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User-Centric Traffic Engineering in Software Defined Networks

Bakhshi, Taimur

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USER-CENTRIC TRAFFIC ENGINEERING IN SOFTWARE DEFINED NETWORKS

by

TAIMUR BAKHSHI

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Abstract

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Taimur Bakhshi

Software defined networking (SDN) is a relatively new paradigm that decouples individual network elements from the control logic, offering real-time network programmability, translating high level policy abstractions into low level device configurations. The framework comprises of the data (forwarding) plane incorporating network devices, while the control logic and network services reside in the control and application planes respectively. Operators can optimize the network fabric to yield performance gains for individual applications and services utilizing flow metering and application-awareness, the default traffic management method in SDN. Existing approaches to traffic optimization, however, do not explicitly consider user application trends. Recent SDN traffic engineering designs either offer improvements for typical time-critical applications or focus on devising monitoring solutions aimed at measuring performance metrics of the respective services. The performance caveats of isolated service differentiation on the end users may be substantial considering the growth in Internet and network applications on offer and the resulting diversity in user activities. Application-level flow metering schemes therefore, fall short of fully exploiting the real-time network provisioning capability offered by SDN instead relying on rather static traffic control primitives frequent in legacy networking.

For individual users, SDN may lead to substantial improvements if the framework allows operators to allocate resources while accounting for a user-centric mix of applications. This thesis explores the user traffic application trends in different network environments and proposes a novel user traffic profiling framework to aid the SDN control plane (controller) in accurately configuring network elements for a broad spectrum of users without impeding specific application requirements.

This thesis starts with a critical review of existing traffic engineering solutions in SDN and highlights recent and ongoing work in network optimization studies. Predominant existing segregated application policy based controls in SDN do not consider the cost of isolated application gains on parallel SDN services and resulting consequence for users having varying application usage. Therefore, attention is given to investigating techniques which may capture the user behaviour for possible integration in SDN traffic controls. To this end, profiling of user application traffic trends is identified as a technique which may offer insight into the inherent diversity in user activities and offer possible incorporation in SDN based traffic engineering.

A series of subsequent user traffic profiling studies are carried out in this regard employing network flow statistics collected from residential and enterprise network environments. Utilizing machine learning techniques including the prominent unsupervised k-means cluster analysis, user generated traffic flows are cluster analysed and the derived profiles in each networking environment are benchmarked for stability before integration in SDN control solutions. In parallel, a novel flow-based traffic classifier is designed to yield high accuracy in identifying user application flows and the traffic profiling mechanism is automated.

The core functions of the novel user-centric traffic engineering solution are validated by the implementation of traffic profiling based SDN network control applications in residential, data center and campus based SDN environments. A series of simulations highlighting varying traffic conditions and profile based policy controls are designed and evaluated in each network setting using the traffic profiles derived from realistic environments to demonstrate the effectiveness of the traffic management solution. The overall network performance metrics per profile show substantive gains, proportional to operator defined user profile prioritization policies despite high traffic load conditions. The proposed user-centric SDN traffic engineering framework therefore, dynamically provisions data plane resources among different user traffic classes (profiles), capturing user behaviour to define and implement network policy controls, going beyond isolated application management.

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Author's Declaration

At no time during the registration for the degree of Doctor of Philosophy has the author been registered for any other University award without prior agreement of the Graduate Committee.

Relevant seminars and conferences were regularly attended at which work was often presented and several papers were published in the course of this research project.

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Chapter 1 Introduction

1.1 Introduction

Software defined networking (SDN) is a relatively new paradigm introduced in the world of computer networking, promising a fundamental shift in the way network configuration and real-time traffic management is performed. While the term itself is relatively new, the salient history of SDN can be traced back to the roots of several traffic engineering and network control mechanisms developed through the years [1-4]. The underlying objective of deriving and centralizing network control primitives has always been to improve the overall network performance and to introduce some degree of network control in at least a particular segment of a much larger network. SDN is seen by many in industry and academia as a culmination of these efforts. The Open Networking Foundation (ONF) [5], an industry consortia furthering work in several areas of SDN development defines the term as "the physical separation of the network control plane from the forwarding plane and where a control plane controls several devices" [1]. The SDN framework tends to make the data plane completely programmable and separated from the control logic and, therefore, eliminates the existing manually intensive regime of fine tuning individual hardware components. The paradigm introduces a centralized control structure, which dynamically configures and governs all underlying hardware based on end user application requirements. Software developers and network managers can collaboratively utilize the high level of network abstraction offered via the control plane to define network resource utilization models and optimize the underlying network fabric according to evolving service requirements. The resulting ease in management of diverse set of network appliances according to real-time traffic conditions provides substantial benefits to operators and managers in efficiently provisioning resources as well as introducing technological and business updates in a seamless fashion. In addition to ONF industry conglomerate, the OpenFlow Network Research Center (ONRC) was created to particularly focus academic research in SDN [6], with major standardization bodies such as ETSI, IETF, ONF, 3GPP, and IEEE itself working towards standardizing different SDN aspects. However, despite the stated advantages and the promise of simplified management, the SDN framework encounters challenges in practical implementation hampering its functionality and resulting performance in avenues ranging from the cloud to data center networking.

The present chapter highlights prominent research challenges in SDN and presents the aims and objectives of the present thesis along with a description of the thesis structure. The remainder of

this chapter is organized as follows. Section 1.2 briefly discusses existing SDN research challenges and initiatives. Section 1.3 details the aims and objectives of the present research. The organization of this thesis is presented in section 1.4.

1.2 Research challenges and intiatives

The continued development and deployment of the SDN framework has presented new application opportunities in several avenues ranging from data centers to wireless communications. The increasing adoption of SDN based traffic engineering solutions in turn has also provided academia and industry with new research challenges. Some of the prominent areas of investigation and initiatives being taken in the context of SDN are summarized as follows.

1.2.1 Application and service improvement

A prominent area of focus in a number of SDN traffic optimization studies has concentrated on improving application and service performance using per-application flow metering [58][59][62]. A range of network control primitives utilizing the centralized SDN control plane have been employed in efforts to offer differentiated quality of service (QoS) primarily for voice and video streaming applications [60][61][115]-[118]. Focus on application and service prioritization has also led to the development of novel SDN based monitoring solutions and test-beds to benchmark individual application and protocol performance metrics [120-124]. A significant amount of work in application and service improvement has also considered the use of information-centric approaches using the centralized SDN control plane to offer optimized content delivery for certain services from caching servers geographically closer to the end user [125-130]. From a physical layer perspective, a few studies have also considered the scope of optimizing service delivery in heterogeneous and legacy networks using the SDN paradigm resulting in enhanced application performance [55][133][134].

The devised SDN traffic management policies in the above studies, are however, typically tied to a single (or set of) applications or services. While isolated service improvement using QoS guarantees may offer increased performance for certain applications such as streaming, voice and other real-time communication, it may also result in negative experience for users having diverse application requirements and when several workload profiles are present in the network. To accurately capture user behaviour, network administrators can instead derive traffic profiles based on user application

trends. The resulting profiles may subsequently be integrated in the SDN framework to allow improved traffic management and resource optimization in view of user trends. Utilizing profiling based traffic engineering, network operators can fully take into account the user-centric mix of applications and implement real-time network policies through the SDN control plane. The scheme may offer significant benefits in terms of devising and applying user-centric network policies over the presently prevalent method of individual application improvement in SDN.

1.2.2 Control plane centralization

In addition to the considerable amount of work undertaken in application and service improvement studies other major areas of investigation in SDN have focused on increasing the real-time scalability of the centralized SDN control plane (controller). The SDN controller(s) while allowing seamless management of the underlying networking gear also introduces additional network latency during device-controller communication requiring optimal placement solutions and suitable redundancy in case of failure [34][35]. The amount of time it takes for network nodes to communicate with SDN controller and subsequent fetching of flow forwarding instructions can affect some end user applications. Additionally, another important aspect is the requirement of having a suitable level of redundancy in controllers and if more than one controller is deployed, placement of controller(s) and latency involved in inter-controller communication channels.

The rapid detection of network topology changes by the control plane when a network node becomes unresponsive is dependent on availability of the communication channel between the controller and network elements [41][42]. The level of control delegated to network devices has, therefore, also been the topic of interest in SDN. The level of control delegated to data plane (switches) depends on business requirements and required redundancy; sometimes allowing both SDN based centralized control as well as legacy switching and routing capability for fail-safe operation. There is no perfect scheme and the resulting solution is highly dependent on trade-offs between operational requirements, costs and speedy re-convergence in case of failures.

1.2.3 Security vulnerabilities

In parallel with application performance and controller placement solutions, a number of studies concentrating on SDN security aspects have sought to address SDN controller vulnerabilities. Centralized control infrastructure offered by SDN may allow malicious traffic to compromise not only the underlying network devices but also the controller, giving away control of the entire

network [46][48][64]. While the technology is relatively new, integration with existing security technologies is either absent or needs to be custom aligned to the SDN framework [43]. Administrators therefore, need to focus on permitting access to management traffic in an intelligent manner as well as segregate traffic from several organizations in multi-tenant deployments such as cloud environments to contain and address security incidents.

1.2.4 Standardization efforts

Finally, with regards to standardization efforts, the SDN paradigm may be easier to implement with a standard set of application programming interfaces (APIs) and protocols. However, such standardized protocols may not work in all cases and diversity in SDN programming interfaces will nonetheless grow. For example, while the majority of vendors have opted for the OpenFlow [17] open standard as their primary choice for data-control plane southbound protocol, industry giants like Juniper and Cisco have selected other solutions such as XMPP [20] and OpFlex [63] to ensure that customers are limited to their technology solution. There are no standard network operating systems, routers or switches as such to be specifically used for SDN and multiple vendors have come up with proprietary technologies in each plane of the SDN architecture advocating ideal solutions.

1.2.5 Industry pragmatism and operational requirements

If industry finds an easier way to solve the same problems offering automation, real-time programmability, centralized control, improved monitoring, support for virtualization and dynamic provisioning by other methods in future, those methods may win. A prominent historical example of this is ATM vs MPLS [9], where the latter took over as the preferred method, despite several years of development, improvement, and deployment spent on ATM based architectures.

1.3 Aims and objectives

The aim of this research is to investigate the application usage trends among users in different networking environments and to establish whether the existing SDN traffic management solutions focusing on individual service improvement (application flow metering), may lead to performance penalties for users frequenting a diverse set of applications. Furthermore, the research aims to propose a user behaviour profiling framework that can accurately capture user application trends

and integrate user traffic profiles in the SDN control plane, leading to user-centric traffic management policies.

In order to achieve this, the research work is divided into the following distinct objectives.

1. To compose a comprehensive review of state-of-the-art in software defined networking technologies and the inherent traffic management approaches.
2. To investigate the diversity of user activities by profiling user traffic and the potential benefits of integrating user-centric (profiling based) controls in the software defined networking framework.
3. To design and propose a method for extracting user traffic profiles in different network environments, focusing on residential and enterprise networks, and analyse temporal variation in the derived profiles for subsequent utilization in an SDN traffic management solution.
4. To propose a novel SDN traffic control framework utilizing the derived profiles in monitoring and managing the respective SDN environment including residential and enterprise networking.
5. To benchmark effectiveness of the proposed user-centric (profiling) controls by carrying out a series of simulation tests in each network setting and monitoring network performance metrics under varying traffic conditions.

1.4 Thesis organization

The organization of this thesis as follows. Chapter 2 presents a comprehensive review of state-of-the-art in software defined networking and the remaining chapters are divided into two logical parts. Part 1 discusses Residential Traffic Management in SDN (chapter 3, 4, 5) and Part 2 concentrates on Enterprise Traffic Engineering (chapter 6, 7, 8). A brief description of each chapter is summarized below.

Chapter 2 begins by reviewing a brief history of complementing technologies leading to the development of SDN along with a discussion of popular SDN protocols, platforms, and application avenues. The review seeks to highlight the benefits of centralized control and programmability offered by SDN. Existing traffic engineering solutions are discussed, which primarily target individual application performance, and the need for user oriented network policy controls that can

provide the administrator with a more meaningful traffic management primitive is identified. Furthermore, due to the relatively early phase of SDN technology development and deployment some notable issues in SDN design, scalability, and security are also considered.

Chapter 3 presents the beginning of Part 1, focusing on SDN based traffic management in residential networks and discusses the feasibility of deriving user traffic profiles from network flow measurements. For this purpose user traffic profiling is carried out on traffic generated from individual user premises in a residential building using unsupervised k-means cluster analysis. The initial work uses IP and port-based mapping of popular Internet applications to identify user traffic flows. The extracted profiles present significant discrimination in user activities, establishing the need for going beyond isolated application improvement, which may otherwise penalize certain users (profiles). The chapter also presents some initial ideas on the utilization of user traffic profiles in SDN based traffic controls.

Chapter 4 further builds on the user profiling methodology and evaluates the stability of the extracted user traffic profiles in the residential network employed in **chapter 3**. Using updated traffic flow measurements, different clustering techniques are also evaluated, aiming to identify the approach that leads to a more meaningful set of user traffic classes (profiles). The profiles derived using k-means clustering remain significantly better in terms of expressing describing user trends. The study further investigates the inter-profile transitions among user devices belonging to the same user premises, reporting an overall high level of stability for subsequent utilization in SDN based traffic management.

Chapter 5 provides a novel traffic management framework for residential settings using software defined networking. The study designs an SDN traffic management application for dynamic bandwidth allocation among multiple residential users according to a profile priority primitive defined by the residential network administrator/ user. The residential SDN controller and traffic management application in turn employs hierarchical token bucket queueing to dynamically assign per user bandwidth between the service provider and residential gateway router. Using the previously derived user traffic profiles from **chapter 4**, simulation tests are carried out under varying traffic conditions (user loads) to evaluate the effectiveness of the proposed approach in catering to prioritized users (profiles).

Chapter 6 presents the beginning of Part 2, focusing on enterprise traffic management using SDN framework. This chapter proposes a real-time application traffic classification approach using flow based measurements. The study focuses on the improvement of classifying user traffic flows from the relatively basic IP address and port based traffic identification used in **chapter 3** and **chapter 4** to an automated machine learning based classification. The study investigates the features in typical flow measurements (NetFlow) and designs a two-phase traffic classifier using unsupervised cluster analysis in tandem with supervised decision tree training to yield optimal per-flow classification accuracy. The resulting classifier is validated against flows from fifteen popular Internet applications reporting high classification accuracy for the examined applications. The chapter concludes by recommending the extension of the proposed method to other applications to achieve highly granular real-time application flow classification and applying the derived classifier in future user traffic profiling and traffic classification studies.

Chapter 7 investigates and evaluates the use of the OpenFlow protocol for traffic profile derivation in campus based SDN. The study assesses the OpenFlow protocol features to derive user traffic profiles for network monitoring and management in campus network environments. The investigation aims to utilize and collect OpenFlow traffic statistics via the SDN control plane (controller), eliminating reliance on external flow accounting methods (such as NetFlow) in campus networking where network devices may be geographically dispersed and operators can benefit from a centralized user profiling mechanism. A test campus network access switch is used for collection of OpenFlow based traffic statistics and fed into the previously derived traffic profiling mechanism. The derived profiles are analysed and benchmarked for stability to ascertain their viability of network monitoring and management in the campus environment. Additionally, the study uses simulation tests to appraise the management overhead of the proposed approach.

Chapter 8 presents a novel traffic profiling and network control framework for the data center (DC) SDN. The study profiles user activity in an enterprise network, segregating users into different traffic profiles based on varying usage of enterprise data sources and highlights the performance caveats the end users may experience due to conventional DC load balancing techniques. A novel user profiling based traffic management scheme is, subsequently proposed for the DC environment, utilizing operator defined global (user) profile and application hierarchy to manage external and internal DC traffic. The proposed framework tracks real-time profile memberships and dynamically configures the individual DC network elements via the SDN control plane (controller). A series of simulation tests are carried out using different user loads to compare the design performance of

the derived user profiling based solution against conventional load balancing schemes. Furthermore, the chapter concludes by evaluating the real-time scalability and management overhead of the proposed approach.

Finally, **Chapter 9** presents the conclusions from this research, highlighting the project achievements and limitations. Future research and development related to the work carried out in thesis are also suggested in this concluding chapter.

Chapter 2 Software Defined Networking Technologies

2.1 Introduction

Computer networks consist of a diverse number of network devices serving several functionalities ranging from security and access control to load balancing and supporting a range of distributed and complex protocols. Changing application and traffic demands necessitate that administrators update network parameters, involving manual translation of high level-policies into low-level device configuration commands. In addition to being repetitive and prone to errors, the underlying lack of automation in network management hinders quick provisioning for relatively new applications such as cloud services. Present network virtualization and automated device programmability mechanisms, although ease network administration and allow some degree of dynamic scalability, they remain far from an ideal solution. Software defined networking on the other hand, as mentioned earlier in chapter 1 decouples the network into a management and traffic forwarding plane. The paradigm allows for both real-time network programmability as well as the integration of virtualized network functions [1][2]. Continued adoption of SDN, however, greatly depends on the development of its underlying constituent technologies. Despite being a relatively new, industry and academia has been involved in furthering the SDN paradigm through the development and deployment of new SDN-specific as well as legacy communication protocols and platforms in the SDN ecosystem. The present chapter examines state-of-the-art in software defined networking by providing a brief historical perspective of the field as well as detailing the SDN architecture. Prominent SDN communication protocols, the controller and switch platforms in use as well as tools for SDN simulation and development are reviewed. Furthermore, major operational challenges and recently proposed solutions are presented in detail to provide a comprehensive discussion of issues such as application-level traffic prioritization, real-time SDN scalability and security.

The remainder of this chapter is organized as follows. Section 2.2 presents provides a brief background to SDN and complementary technologies while also highlighting present day networking requirements that led to the emergence of SDN. Section 2.3 discusses the SDN architecture. A detailed review of prominent communication APIs and protocols being deployed in relation to the SDN framework are detailed in section 2.4. Section 2.5 reviews the available SDN controller and switch platforms, while SDN simulation and development tools are discussed in Section 2.6. Section 2.7 summarizes the progress in several SDN typical deployment scenarios such

as data centers, campus environments, wireless communications and residential networks. A discussion of key technological and research challenges inherent in the present SDN framework is presented in section 2.8. Final conclusions are drawn in section 2.9.

2.2 Background and complementary technologies

It is rather difficult to examine the etymology of 'software defined networking' as the fundamental requirement of introducing network programmability has been around since the inception of computer networks. The term however, was first coined in an article in 2009 [7], to describe work done in developing a standard called OpenFlow giving network engineers access to flow tables in switches and routers from external computers for changing network layout and traffic flow in real-time. However, technologies supporting the centralization of network control, introducing programmability and virtualization have existed prior to SDN and over the years matured to varying degrees of adoption among operators catering to individual application requirements. The following sub-sections briefly highlight some of these key supporting technologies in centralizing network control, introducing network programmability and virtualizing the network fabric to provide a better understanding of their similarities and inadequacies in comparison with SDN. Table 2.1 gives a summarization of these complementing technologies. A timeline depicting development of key complimentaing and SDN specific technologies is presented in Fig. 2.1.

2.2.1 Centralized network control

Centralization of network control dates back to at least the early 1980s when AT&T introduced the network control point (NCP), offering a centralized database of telephone circuits and out-of-band signalling mechanism for calling card machines [206]. The idea of control and data plane separation was also used in BSD4.4 routing sockets in the early 1990s, allowing route tables to be controlled by a simple command line or by a router daemon [207]. Another significant milestone in the development of centralized network control includes the Forwarding and Control Element Separation (ForCES) project which started as an IETF working group in 2001. ForCES employs a control element to formulate the routing table in traffic forwarding elements [8]. Each control element interacts with one or more forwarding elements, in turn managed by a control and forwarding element manager offering increased design scalability. With the development and wider adoption of generalized and multi-protocol label switching (G/MPLS), network routers were

Table 2.1. Complementary Technologies

Functionality	Control Functions, APIs	Complimentary Technologies
Centralized Control	Centralized /delegated control framework	ForCES [8], PCE [10], OPENSIG [11], NCP [206], BSD4.4 Routing Sockets [207], GSMP [12], 4D [13], Ethane [14], G/MPLS [9]
Network Programmability	Low level network abstraction	Active Networks [18], XMPP [20], DCAN [19]
	High level network abstraction	ALTO [21], I2RS [22], Cisco onePK [23]
	Configuration API	NETCONF [31], SNMP [32], GeoPlex [208]
Virtualization	Network device virtualization and overlays	Tempest [25], VINI [26], Cabo [27], VXLAN [28], NVGRE [29], STT [30], NFV [33]

required to perform complex computations for path determination while satisfying multiple constraints ranging from backup route calculations to using paths which conformed to a given or required bandwidth [9]. Individual routers, however, to a great extent lacked the computing power or network knowledge to carry out the required route construction. Following this, the IETF path computation engine (PCE) working group developed a set of protocols that allowed a client such as a router to get path information from the computation engine, which could be centralized or partly distributed, in every router [10]. The technology has attracted significant interest, having more than twenty-five RFCs at the time of writing. In spite of its benefits, the scheme, however, lacks a dedicated control or path computation engine discovery mechanism and provides only a reactive or on-demand facilitation of information to computation clients. The Open Signalling (OPENSIG) group

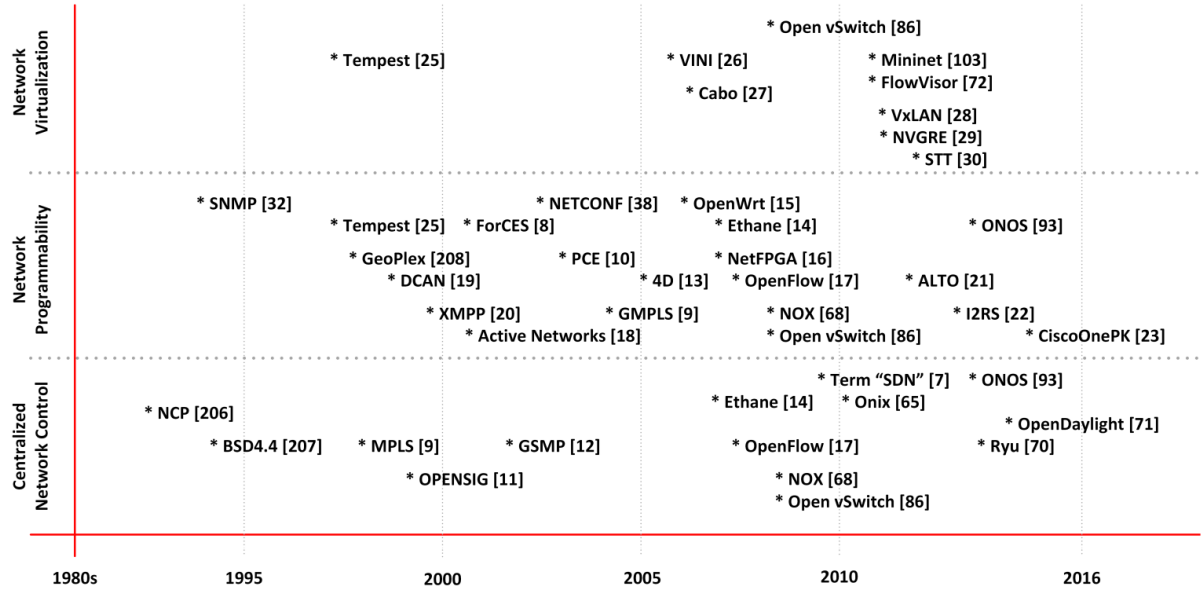


Figure 2.1. Key developments in complementary and SDN-specific technologies

started in 1998 aimed to make the ATM, Internet and mobile networking both programmable as well as open [11]. The group worked towards allowing access to network hardware via programmable interfaces offering distributed and scalable deployment of new services on existing devices. The IETF took this idea to standardize and specify the General Switch Management Protocol (GSMP), a protocol managing network switch ports, connections, monitoring statistics as well as updating and assigning switch resources via a controller [12]. The 4D project, initiated in 2004, proposed network design that separated the traffic forwarding logic and the protocols used for inter-element communication [13]. The framework proposed the control or "decision" plane having a global view facilitated by planes further down the hierarchy responsible for providing element state information and also forwarding traffic. More recently, and a direct predecessor to enabling SDN technology was the Ethane project [14]. Proposed in 2007, the domain controller in Ethane computed flow table entries based on access control policies and used custom switches running on OpenWRT [15], NetFPGA [16] and Linux systems to implement the traffic forwarding constructs. Due to the constraints of requiring customized hardware Ethane, however, was not taken up by many industry vendors as anticipated. In comparison the present scheme for SDN uses existing hardware and vendors are only required to expose interfaces to flow tables on switches with OpenFlow [17] protocol providing capability of controller-switch communication. Growth in centralized network control has not been in insolation and efforts have continued in parallel to bring automation and programmability to the network appliances as examined in the following section.

2.2.2 Real-time network programmability

Network administrators have long yearned for ease in programmability of network devices as the present method of configuration (mainly via CLI) despite being effective is rather slow and requires laborious work in changing configurations, growing significantly with the size of the network. The US defense and advanced research projects agency (DARPA) in the late-1990s envisioned the underlying problems in integrating new technology in conventional networking and the elaborate and tedious re-configurations required hampering acceleration of innovation. The term *active networks* was proposed around the same time and advocated custom computation on packets to significantly reduce pre-determination of traffic forwarding constructs required in individual devices [18]. An example of this would have been trace programs running on routers and the idea of active nodes downloading new service instructions to for example, serve as firewall or offer other application services. However, not having a clear application at the time such as present

day cloud networking and lack of cheap network support, the idea did not fully achieve fruition. Another network programming initiative in the mid-1990s was the Devolved Control of ATM Networks (DCAN) [19]. The underlying aim of DCAN was the designing and development of infrastructure and services required to achieve scalability in controlling and programming ATM networks. The working principle of the technology is that ATM switch control decisions should be decoupled from the devices and delegated to external entities, the DCAN manager. The DCAN manager in turn uses programming instructions to manage the network elements, similar to present day SDN. Another similar project aimed at incorporating programmability in the network elements was AT&T's GeoPlex [208]. The project utilized Java programming language to implement middleware functionality in networking gear. GeoPlex was meant to be a service platform managing networks and services using the operating systems running on Internet connected computers. The resulting soft switch abstraction, however, could not re-program physical devices due to incompatibility with proprietary operating systems running on these devices. Another vital addition to network programmability came in the form of the extensible message and presence protocol (XMPP). XMPP described in RFC6121 works quite similar to SMTP but is targeted at near real-time communication offering additional functionalities of monitoring presence along with messaging [20]. Each XMPP client sets up a connection with the server in the network which maintains contact addresses of clients and lets other clients know when a contact is online. Messages are pushed (real-time) as opposed to polled as in SMTP/POP and the protocol is now being used in data center networking as well as the upcoming Internet of things (IoT) paradigm to manage network elements. Network devices run XMPP clients which respond to XMPP messages containing CLI management requests. Juniper Networks have chosen it as the southbound protocol of choice for the SDN controller to network element (control-data plane) communication in a substantial number of hardware devices.

From a network configuration perspective, legacy technologies such as SNMP [32] and NETCONF [31] have and continue to remain widely deployed in several networking environments. The configuration APIs give administrators the ability to install, change and update the configuration of network devices as well as aid in collating and organizing information about the managed routers, switches and other network devices. Although promising in terms of automating configuration as well as the monitoring of networking gear, the need for bringing further automation and programmability to networks especially emerging cloud and data center environments continues. Offering an even higher level of abstraction from a network administrator or service provider’s perspective is the Application Layer Traffic Optimization (ALTO) protocol. ALTO started by an IETF

working group and originally aimed at optimizing P2P traffic by identifying nearby peers has seen further extension for locating resources in data centers [21]. ALTO clients produce a list of resources, their underlying constraints such as memory, storage, and bandwidth and power consumption and present this information to the server. The ALTO server gathers knowledge about the available resources and allows a detailed orchestration of the network fabric to be used by the running applications. The Interface to the Routing System project (I2RS) of IETF also allows a similar routing strategy and proposes the splitting of traffic management decision-making process between a centralized management system and individual applications [22]. Unlike SDN, I2RS proposes using traditional routing protocols executed on network hardware in parallel to offering centralized control. The scheme uses distributed routing while allowing individual applications to influence routing decisions as required. Developments in network programmability however, have not been limited solely to standardization bodies and workgroups. Lately, technology vendors such as Cisco have also taken up the SDN paradigm to enable programmers to develop applications that can integrate with the network fabric. The Cisco Open Network Environment Platform Kit (Cisco onePK) provides an SDN programmable framework allowing operators to customize traffic flows and visualize network information for easier deployment according to changing business needs [23]. The framework is now being folded in to Cisco's Application Centric Infrastructure (ACI) [24], which seeks to further integrate software and hardware driven by operational requirements.

2.2.3 Network virtualization

Network virtualization can be described as the representation of one or more network topologies residing on the same infrastructure. Virtualization has seen several phases of deployment from relatively basic VLANs, to various intermediate technologies and test-beds. A few milestone projects worth mentioning include Tempest, VINI and Cabo. Tempest originated at Cambridge in 1998 and proposed the idea of switch virtualization as well as a separation of control framework from switches as well as [25]. Tempest proved to be an early attempt at decoupling traffic forwarding and control logic, specifically in the context of ATM networks. Similar to present day SDN, Tempest project put emphasis on having open programming interfaces and additional support for network virtualization. On a slightly separate strand, network virtualization focusing on testing new protocols and services was the Virtual network infrastructure (VINI). VINI came to light in 2006, offering researchers a virtual networking testbed to deploy and evaluate multiple ideas simultaneously on different network topologies using realistic routing software, user traffic and networking events [26]. A VINI-enabled network also allowed operators to run multiple protocols

on the same underlying physical network, independently controlling traffic forwarding in individual network devices for each virtual switch. For service providers relying on hardware infrastructure from multiple infrastructure vendors, the Cabo project in 2007 proposed a separation of infrastructure from services [27]. Using virtualization and programmable traffic routing, CABO offers the ability for service providers to run multiple services on networking gear belonging to disparate infrastructure providers. Virtualization in presently deployed networks offers improved resource sharing which can either be multiple logical routing devices on a shared platform allowing resource slicing such as dedicated memory allocation or independent traffic forwarding software utilities, all running on the same general purpose computing hardware.

In addition to device virtualization projects, network overlays such as the Virtual Extensible Local Area Network (VXLAN) technology were developed as a means to mitigate the limitations of present networking technology and allow service extensibility in larger data center and cloud deployments [28]. VXLANs utilize MAC-in-IP tunnelling, creating stateless overlay tunnels between endpoint switches performing encapsulation. Similar to VXLAN is the Network Virtualization using GRE (NVGRE) [29]. NVGRE also embeds MAC-in-IP tunnelling, with a slight difference in the header format. VXLAN packets use UDP-over-IP packet formats sent as unicast between two endpoint switches to assist load balancing while NVGRE uses the GRE standard header. Another relatively new virtualization technique is the Stateless Transport Tunnelling (STT) again using MAC-in-IP tunnelling [30]. While the general idea of a virtual network exists in STT, it is however, enclosed in a more general identifier called a context ID. STT context IDs are 64 bits, allowing for a much larger number of virtual networks and a broader range of service models. STT attempts to achieve performance gains over NVGRE and VXLAN by leveraging the TCP Segmentation Offload (TSO) found in the network interface cards (NICs) of many servers. TSO allows large packets of data to be sent from the server to the NIC in a single send request, thus reducing the overhead. STT, as the name implies, is also stateless and packets are unicast between tunnel end points, utilizing TCP in a stateless manner (without TCP windowing scheme) associated with TSO. In addition to network virtualization, services such as DNS, access control, firewalls and caching can also be decoupled from the underlying virtual network to solely run as software applications on high volume dedicated hardware and storage. Such virtualization of network functionality (NFV) generally aims at reducing the operational and capital expenditure for organizations minimizing dedicated hardware requirements [33].

2.2.4 Requirement for SDN

While the network virtualization technologies promise greater benefits when compared to conventional and legacy protocols and architectures, the growth in Internet, public and private network infrastructure, as well as the evolving range of applications requires a comprehensive re-vamping of the existing networking framework. The use of distributed protocols and coordination of changes in conventional networks remains incredibly complex involving the implementation of distributed protocols on the underlying network hardware to facilitate multiple services from traffic routing, switching and guaranteeing quality of service applications to providing authentication. Keeping track of the state of several network devices and updating policies becomes even more challenging when increasingly sophisticated policies are implemented through a constrained set of low-level configuration commands on commodity networking hardware. This frequently results in misconfigurations as changing traffic conditions require repeated manual interventions to reconfigure the network, however, the tools available might not be sophisticated enough to provide enough granularity and automation to achieve optimal configurations.

The fundamental requirement of an overall framework that catered for a range of operational requirements such as ease of programmability, dynamic deployment and provisioning while fully facilitating an innovative range of applications and services such as the cloud, dictated newer network architecture capable of fulfilling these prerequisites. The following list details the technology and operational concerns eventually leading to development of the SDN traffic management framework corroborated during this review.

- **Automation:** An increased level of automation to reduce the overall operational expenditure as well as facilitate effective troubleshooting, reducing unscheduled downtimes, ease of policy enforcement and provisioning of network resources and corresponding application workloads as required.
- **Dynamic Scalability:** Dynamically changing the size of the network, updating the topology and the assigned network resources, which may be further aided by network virtualization
- **Orchestration:** Orchestrating control of the complete range of network appliances by hundreds or even thousands such as in data centers or larger campus network environments.
- **Multi-tenancy Support:** With growing proliferation of cloud based services, tenants prefer complete control over their addresses, topology, routing and security and consequently there is a requirement to separate the infrastructure from tenant hosted services.

- **Open APIs:** Users having a full choice of modular plug-ins, offering abstraction, defining tasks by APIs and not being specifically concerned about implementation details. For example, communication between two nodes may be furnished without the specification of the exact protocol.
- **Greater Programmability:** A fundamental requirement in present network provisioning is the ability to change device behaviour and configuration in real-time according to the prevalent traffic conditions.
- **Improved Performance:** A control framework offering the ability to incorporate innovative traffic engineering solutions, capacity calculation, load-balancing and a higher level of utilization to reduce carbon footprint.
- **Multiple Service Integration:** The ability to include multiple services seamlessly such as load-balancers, firewalls, intrusion detection systems which can be provisioned on-demand and placed in the traffic path as and when required.
- **Network Virtualization:** The ability to provision network resources without concerns about the location of individual components such as routers, switches, etc.
- **Visibility and Real-time Monitoring:** Improving the real-time monitoring and connectivity of devices.

A centralized view of the distributed network through the SDN control plane provides a more efficient orchestration and automation of network services. While legacy protocols can react after services come online, SDN can foresee additional service requirements and take pro-active measures to allocate resources. Furthermore, SDN based network applications deliver highly granular network policies on per-application traffic flows. The following section examines the architecture of the SDN framework in detail.

2.3 Architectural overview

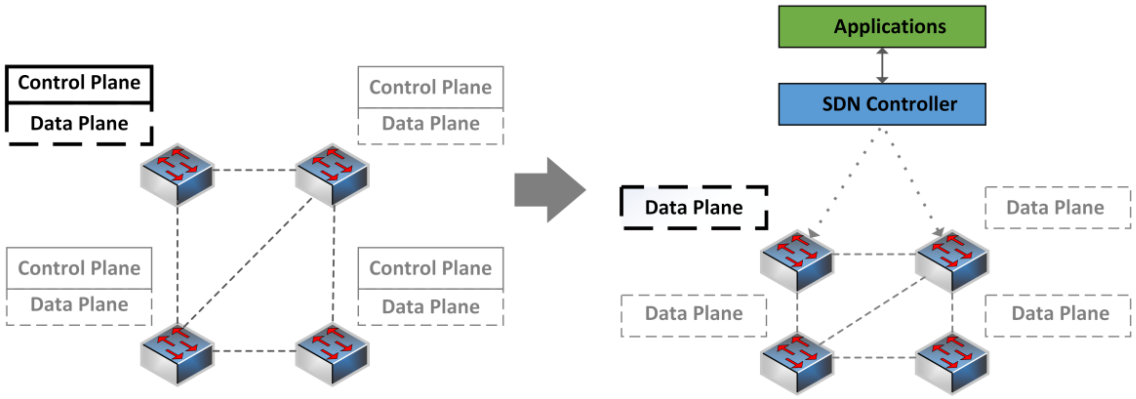
The basic architecture of SDN utilizes modularity based abstractions, quite similar to formal software engineering methods [1][3]. A typical SDN based network architecture divides processes such as configuration, resource allocation, traffic prioritization and traffic forwarding in the underlying hardware in three basic layers namely application, control and data planes. Each of the planes has well defined boundaries, a specific role, and relevant application programmable interfaces (APIs) to communicate with adjacent planes. A comparison between the existing

distributed traffic control of individual devices and the centralized SDN architecture is illustrated in Fig 2.2. The key components of the framework entail the following.

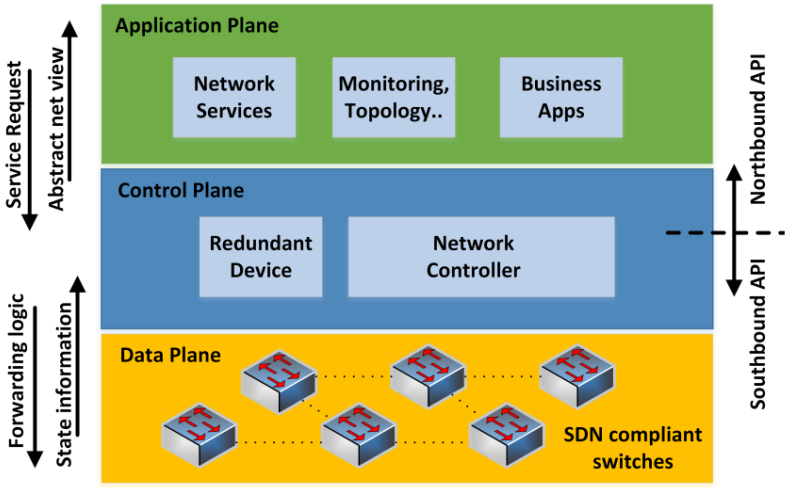
- **Data (forwarding) Plane:** The data plane is a set of network components which can be switches, routers, virtual networking equipment, firewalls, etc. The sole purpose of data plane is to forward network traffic as efficiently as possible based on a certain set of forwarding rules which are instructed by the control plane. SDN architecture makes the networking hardware rather inoculate by removing forwarding intelligence and isolated configuration per network element and moving these functionalities to the control plane. Communication between data and control planes is achieved by APIs (southbound). At present the OpenFlow protocol [17], serves as a prominent southbound communication protocol supported by several vendors including the ONF [5].

- **Control Plane:** The control plane is responsible for making decisions on how traffic would be routed through the network from one particular node to another based on end user application requirements and communicating the computed network policies to the data plane. The central component of a control plane is the SDN controller. An SDN controller translates individual application requirements and business objectives such as the need for traffic prioritizing, access control, bandwidth management, QoS etc. into relevant forwarding rules which are communicated to data plane components. Based on the size of the network there can be more than one SDN controller to provide additional redundancy [34][35]. By introducing network programmability through the control plane, it becomes possible to manipulate flow tables in individual elements in real-time based on network performance and service requirements. The controller gives a clear and centralized view of the underlying network giving a powerful network management tool to fine tune network performance.

- **Application Plane:** The application plane comprises of network and business applications. An abstract view of the underlying network is presented to applications via a controller northbound API. The level of abstraction may include network parameters like delay, throughput, and availability descriptors giving the applications a wider view of the network [58]-[62]. Applications in return request connectivity between end nodes and once the application or network services communicate these requirements to the SDN controller, it



(a) De-centralized Control



(b) Centralized Control

Figure 2.2. Diagram illustrating (a) Decentralized Network Control and (b) SDN based Centralized Control

correspondingly configures individual network elements in the data plane for efficient traffic forwarding. Centralized management of network elements provides additional leverage to administrators giving them vital network statistics to adapt service quality and customize network topology as needed [58], [59], [62]. For example, during periods of high network utilization certain bandwidth consuming services such as video streaming, large file transfers, etc. can be load balanced over dedicated channels. In other scenarios, such as during an emergency (fire alarms, building evacuations, etc.) services such as VoIP can take

control of the network i.e. telephony taking precedence over everything else. A brief overview of the SDN controller and control-service communication protocols is presented in the following sections.

2.4 Communication APIs

SDN framework utilizes the link between the data and control plane to control traffic forwarding elements. The link should therefore, present high availability as well as security. One of the major southbound protocols in this category is the OpenFlow protocol [17]. The protocol offers communication between the switches and the controller(s) using Transport Layer Security (TLS) and certificate exchanges between the switches and the controller. In addition to OpenFlow protocol SDN implementations may also utilize legacy technologies such as XMPP [20], Cisco OpFlex [63] or even legacy NETCONF [31] for controller-switch communication.

In addition to controller-switch communication, external applications and services may require information about the network topology, state and network device capabilities to manage traffic forwarding and define network policies. However, unlike the controller-switch communication protocols, there is no standardized northbound programming interface and solutions are applied on an ad-hoc basis depending on controller support and compatibility [1][2]. The architecture and APIs (northbound) of SDN applications vary between vendors. Some vendors have incorporated SDN controllers inside applications while others have defined custom northbound APIs for policy translation between controllers and proprietary higher application layer SDN services. Prominent programming paradigms such as the Representational State Transfer (RESTful) protocol [36] and Java based Open Services Gateway Interface (OSGI) [37] have found increasing applicability across a wide range of controller platforms to serve northbound (controller-application) communication requirements.

2.4.1 Southbound communication protocols

Southbound APIs provide the network control required by the SDN controller to dynamically make network changes as per real-time requirements. The OpenFlow protocol [17] maintained and updated by ONF [5] is the first and most prominent southbound communication interface. OpenFlow defines controller-data plane interaction facilitating administrators to manage traffic

according to changing business requirements. Using OpenFlow, flow forwarding constructs can be added and removed in switch flow tables to make the network fabric more responsive to service demands. A number of networking vendors have signed up to support implementation of OpenFlow including Big Switch, Arista, Brocade, Dell, IBM, NoviFlow, HP, Cisco, Extreme Networks and NEC among others. While OpenFlow is quite well-known it is not the only one available or under development. Besides, the OpenFlow protocol, Cisco OpFlex [63] has gained momentum among southbound APIs. The extensible messaging and presence protocol (XMPP) [20] has found a certain degree of traction for further deployment especially in hybrid SDN which uses a bulk of legacy protocols such as OSPF, MPLS, BGP, and IS-IS to interconnect with SDN architecture. The operational functionality of OpenFlow, XMPP and OpFlex are further detailed in the following sub-sections.

a) OpenFlow protocol

OpenFlow is a major Southbound API developed in the early stages of SDN paradigm and is meant to communicate control messages between the SDN controller and the networking components in the data plane [17]. A typical OpenFlow compatible switch comprises of one or more flow tables, matching incoming flows (and packets) with policy actions such as prioritization, queueing, packet dropping etc. The SDN controller can manipulate the flow tables either in (a) real-time, reactively, by interrogating the controller to ask for forwarding information (e.g., if the forwarding path for a packet is unknown) or (b) proactively, by sending complete flow entries based on requirements dictated by higher applications residing in the application plane. The OpenFlow pipeline processing through flow tables is depicted in Fig. 2.3 and a descriptive table with flow table entries is given in Table 2.2.

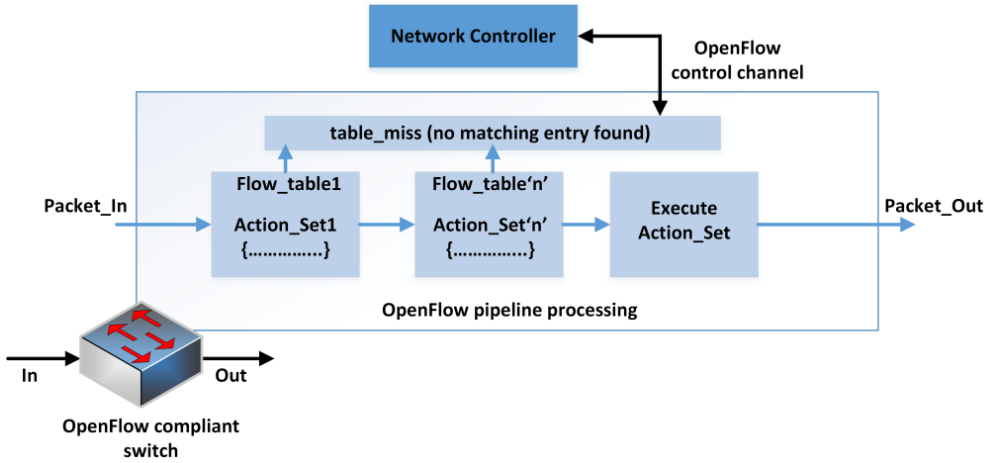


Figure 2.3. OpenFlow Pipeline Processing

Table 2.2. OpenFlow Flow Table Entries

Parameter	Match Fields	Counters	Instructions
Functionality	Matching packet headers, ingress ports, instructions and previous table meta data	Update respective counters based on packet matches	Apply per-flow actions
Purpose	Traffic segregation for further processing	Measuring flow statistics, real-time traffic monitoring	Flow routing, metering, queueing, QoS, etc.

OpenFlow allows multiple flow tables to offer specific control instructions to be applied in a sequential order and flow segregation. Once a packet arrives at the switch, matching is performed in either a single flow table and sent to its destination (outgoing port) or sent to other flow tables as dictated by the network control logic provided by the controller. Flow matching occurs on the basis of a prioritization mechanism in table entries, with the top matching (first match) entry in the flow table and corresponding action to be executed. If no match is found (called a "table miss") the packet is either dropped or a request for processing instructions is sent to the controller (*packet_in*). The controller in turn has the prerequisite knowledge regarding location of the target destination, such as campus server(s) or the Internet gateway discovered during service initiation. The controller sends a *packet_out* message to the respective switch and *flow_mod* messages to each switch along the destined path of the flow describing forwarding actions.

Packets transverse switch flow tables in the form of metadata communicated between different tables. Flow entries can also point the packet to a set of particular group actions. Group actions allow a set of complex policies to be executed on the packets compared to flow tables such as route aggregation, multicasting, etc. Packets arriving at the ingress port of a switch are generically processed in the following sequence.

1. Highest priority matching flow entry in the first flow table is found based on ingress port, metadata and packet headers. Priority is calculated on a top to bottom approach with entries at the top carrying higher priority.

2. Relevant instructions are applied:
    - Modify the packet as instructed in actions list.
    - Update the action set by adding and deleting actions in the actions list.
    - Update metadata.
3. Send match data and action set to the next table for further processing.

The fundamental difference between an action list and action set is the time of execution [5]. An action list is executed as soon as a packet leaves the flow table to make necessary changes to this data whereas an action set keeps accumulating actions which are executed once the packet(s) transverses through all relevant flow tables. Flow tables are assigned numbers in sequence and match data along with its action set can generally only be sent from a table of lower sequence to higher, assuring that packets move in forward direction instead of backward through a switch. The flow-entries, once installed in switch tables, conform to pre-set *idle_timeout* and *hard_timeout* values. An OpenFlow compliant switch maintains a TLS control channel with the SDN controller and periodically sends keepalive "hello" messages to communicate state information. The communication uses the TCP protocol to ensure reliability in message delivery between the controller and switch. Well known TCP ports for OpenFlow traffic are 6633 and 6653 (official IANA port since 18-07-2013) [17]. OpenFlow versions have evolved over the past few years offering bug fixes and enhancements. The latest version available at the time of writing is v1.5 [17].

The OpenFlow protocol also allows multi-part read-state messages to retrieve traffic statistics from switches via the SDN controller. The three prominent message types used are (i) Controller-to-switch, initiated by the controller to manage and inspect switch state, (ii) Asymmetric, initiated by the switch to notify of network events and (iii) Symmetric, initiated by either entity to keepalive the control channel [17]. Each message comprises of further sub-types for specific actions. Some well-known message types and their size are presented in Table 2.3. The controller, however, does not orchestrate flow-forwarding behaviour based on any collected statistical information on its own. Using the controller northbound programming interface (API), allows administrators to poll OpenFlow switch counters and utilize this information in a monitoring solution to manage the underlying network.

Table 2.3. OpenFlow Message Specification

Type	Message	OpenFlow Switch Conformance Spec. v1.3.1	Size
Flow forwarding and control	Packet_In	OFPT_PACKET_IN	160 bits+ first flow packet
	Packet_Out	OFPT_PACKET_OUT	160 bits+ update packet
Statistics, counter polling	Table_Stat	OFPC_TABLE_STATS	32.3 bytes
	Flow_Stat	OFPC_FLOW_STATS	448 bits
Switch event	Flow_Rem	OFPT_FLOW_REMOVED	352 bits

b) Extensible Messaging and Presence Protocol (XMPP)

The extensible messaging and presence protocol (XMPP) was originally designed as a general communications protocol offering messaging and presence information exchange among clients through centralized servers [20]. XMPP remains quite similar to simple message transfer protocol (SMTP), however, the schema is extensible through XML encoding for user customization and additionally the protocol provides near real-time communication. Each XMPP client is identified by an ID, which can be as simple as an email address. Client machines set up connections to advertise their presence to a central server, which maintains contact addresses and may inform other contacts know that a particular client is online. Clients communicate with each other through chat messages which are pushed as opposed to polling used in SMTP/POP emails. The protocol is an IETF standardization of the Jabber protocol and has been defined for use with TCP connections in RFC 6121. A number of open source XMPP implementations are also available with variations being used in applications including Google, Skype, Facebook and many games. The protocol has found new applicability in hybrid SDN, Internet of Things (IoT) and data centers and is being used for managing individual network devices. Network devices run XMPP clients which respond to XMPP messages containing CLI management requests. In data centers, every object such as virtual machine, switch and hypervisor can have an XMPP client module awaiting instructions from XMPP server for authentication and traffic forwarding as shown in Fig. 2.4. Upon receiving instructions, the clients update their configuration as per server request(s).

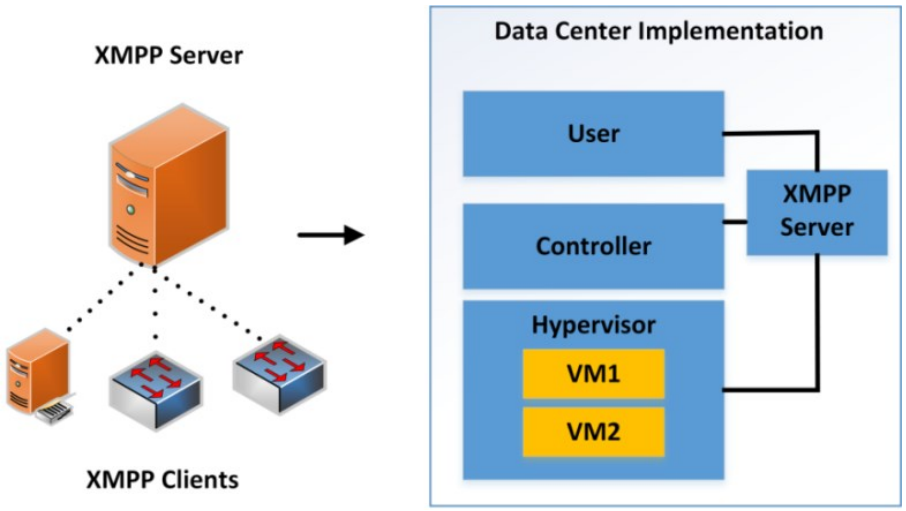


Figure 2.4. XMPP Client-Server Communication

While XMPP is defined in an open standard and follows an open systems development and application approach allowing interoperability among multiple infrastructures, it also suffers a few weaknesses. The protocol requires an assured message delivery extension to guarantee QoS of message exchanges between the XMPP client and the server. Additionally, the protocol does not allow end-to-end encryption, a fundamental requirement in the modern dispersed and multi-tenanted network architectures. Extensions are, however, available dealing with assured message delivery, and the encryption of messages.

c) Cisco OpFlex

Cisco OpFlex is another example of a southbound SDN protocol facilitating control-date plane communication with a goal of becoming a standard, enabling policy application across multiple physical and virtual environments. In comparison with OpenFlow protocol, which centralizes all the network control functions using the SDN controller, the Cisco OpFlex protocol instead concentrates primarily on implementing and defining the policies [63]. The reason for enhanced focus on policies is to remove the controller scalability and control channel communication from becoming the network bottleneck and pushing some level of intelligence to the devices using legacy protocols. The framework allows policy definition within a logical, centralized repository in the SDN controller, and the OpFlex protocol communicates and enforces the respective policies within a subset of distributed elements on the switches. The protocol allows bidirectional communication of policies, networking events and statistical monitoring information. Real-time provision of information may in turn be used to make networking adjustments. The switches contain an OpFlex agent supporting the Cisco OpFlex protocol. Cisco is currently developing an open source, interoperable OpFlex agent. Some of the industry giants, including Microsoft, IBM, F5, Citrix and Red Hat, have shown commitment to embedding OpFlex agent in their product lines [63]. OpFlex relies on traditional and distributed network control protocols to push commands to the embedded agents in switches. One of the main reasons for the early adaption of OpenFlow has been the level of control it can offer to developers for designing network control applications with minimal support from network vendors. Therefore, in order to standardize OpFlex, Cisco has also submitted the protocol to IETF standardization process and several vendors are presently working to standardize as well as increase the adoption of the protocol [63].

2.4.2 Northbound communication protocols

Since the inception of SDN, a number of networking vendors have started actively developing SDN oriented applications with the aim of reducing the OPEX and CAPEX of future IT network infrastructures. The applications themselves vary in scope with some providing a comprehensive network monitoring and control solution while others solely target a particular aspect of load balancing, security and traffic optimization through SDN controllers. The architecture and APIs (northbound) of SDN applications vary between vendors. Some have incorporated SDN controllers inside applications while others have defined custom northbound APIs for policy translation between controllers and their own higher application layer SDN services. As per the ONF SDN framework [1], applications might act as an SDN controller in their own right or liaise with one or more SDN controllers to gain exclusive control of resources exposed by controllers. Applications can exist at any level of abstraction with a general perception that the further north (higher) we go in SDN framework, the greater the level of abstraction. A specific distinction between applications and controller is not precise [2][3]. A controller-application interface may mean different things to different vendors. However, the fundamental principle of abstracting network resources and presenting network state to applications provides real-time network programmability, the cornerstone of SDN.

The ONF constituted a special working group in June 2013 towards standardizing the northbound interface (NBI) architecture across the industry [5]. Although there is considerable debate within industry whether such a standardized interface is even required, the benefits of having an open northbound API are also significant. Open northbound API allows developers from different areas of industry and research to develop a network application, as opposed to only equipment vendors. It also gives network operators the ability to quickly modify or customize network control. Despite initially proposing it, the ONF consortium has, therefore, subsequently avoided northbound API standardization to allow maximum innovation and experimentation. As a direct result, more than 20 different SDN controllers that are currently available feature varying northbound APIs based on the needs of the applications and the orchestration systems residing above. There is a chance there will never ever be a standardized northbound API. Routing and switching vendors that traditionally rely on network-based applications and features to differentiate their hardware are positioning themselves to maintain profitability in the SDN arena. These vendors may invest in custom software, while using standard southbound protocols such as OpenFlow to run concurrently alongside their operating system and complement the existing control plane. The result would definitely be a

complex and crowded SDN ecosystem. The following subsections review the two popular northbound APIs, the RESTful [36] and Java based OSGi [37] interface prevalent in SDN controllers.

a) Representational State Transfer (RESTful)

Representational state transfer, or simply REST, follows the software architecture style developed for World Wide Web consortium (W3C) encompassing all client-server communications. The concept was originally introduced by Roy Fielding in [36]. The main goals of the scheme are to offer scalability, generality, and independence and allow the inclusion of intermediate components between clients and servers to facilitate these necessary functionalities. Both clients and servers can be developed independently or in tandem, there is no particular necessity to have both developed by same vendor. A schematic diagram representing RESTful calls is shown in Fig. 2.5. The server component is stateless and clients keep track of their individual states to allow scalability. Server responses can be cached for a specified time. Every entity or global resource can be identified with global identifiers such as URIs and is able to respond to create, read, update and delete (CRUD) operations. The uniform interface for each resource is GET (read), POST (Insert), PUT (write) and DELETE (remove). Data types can define network components such as controller, firewall rule, topology, configuration, switch, port, link and even hardware. RESTful is prevalent in most controller architectures as the northbound interface of choice along with Java APIs. One of the major drawbacks of RESTful however, is the lack of public subscription or live feed informing the SDN controller of network state changes. Like HTTP, REST cannot determine when a page has changed and requires frequent refresh. Application developers therefore, use loop calls at periodic time intervals to retrieve and subsequently post updates to individual switches based on pre-defined policies.

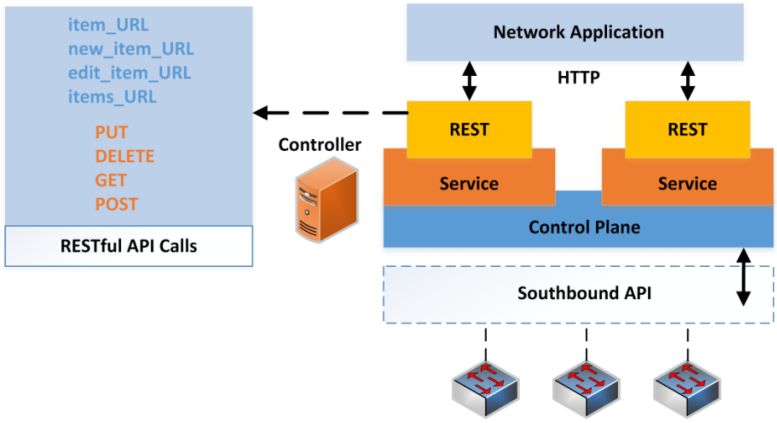


Figure 2.5. RESTful Application Programming Interface (API)

b) Open Services Gateway Initiative (OSGi)

The open services gateway initiative (OSGi) is a set of specifications for dynamic application composition using reusable Java components called bundles [37]. Bundles publish their services with OSGi service registry and can find/use services of other bundles as depicted in Fig. 2.6. Bundles can be installed, started, stopped, updated and uninstalled using a lifecycle API. Modules define how a bundle can import/export code. The security layer handles security and execution environment defines what methods and classes are available in a specific platform. A bundle can get a service or it can listen for a service to appear or disappear. Each service has properties that allow other services to select among multiple bundles offering the same service. Services are dynamic and a bundle can decide to withdraw its service, which will cause other bundles to stop using it. Bundles can be installed and uninstalled on the fly. The OpenDaylight project [71] is one major example of a SDN controller platform built using the Java based OSGi framework. OSGi allows the starting, stopping, loading and unloading of Java based network (module) functionalities. In comparison, platforms such as Ryu [70], do not offer OSGi support and the controller has to be stopped and restarted with the needed modules or a custom REST method is built with all the required functionalities included to avoid controller restarts. A few other SDN platforms supporting OSGi include Beacon [75], Floodlight [76] and ONOS [93].

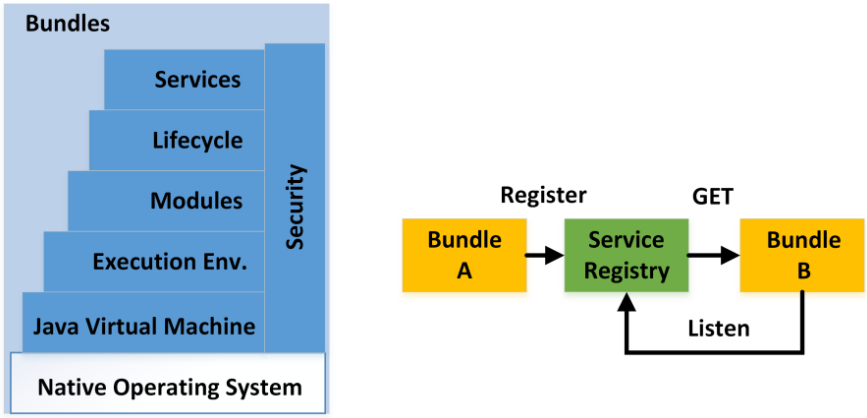


Figure 2.6. Open Services Gateway Initiative (OSGi)

2.5 Network controllers and switches

The SDN controller provides a programming interface for administrators to control the underlying network elements. Network administrators and application developers can collaboratively use the controller to perform management tasks as well as introduce newer functionalities such as flow metering for QoS, re-routing and load-balancing as well as providing access control. The level of abstraction offered to the operator, therefore, depicts the underlying network switches as a single system which can be updated in real-time according to service requirements. The SDN framework can be applied to a wide range of services and heterogeneous networking technologies as well as media including virtual and physical networking gear and wired and wireless networks. Since the inception of SDN, there have been a number of controller platforms developed for the purposes of academic research as well as several vendors producing proprietary carrier-grade solutions. The support for southbound and northbound APIs in controller platforms, however, varies with each platform [40]. While the previous sections discussed about the architectural components and interactions, this section refers to the physical components and how the architecture links to an actual implementation. SDN controller and SDN-compliant switch features are elaborated further in the following sub-sections.

2.5.1 SDN controllers

The SDN controller maintains and applies network policies as required by higher applications and services, and translates and configures these policies in individual network devices. As mentioned earlier, once a packet arrives at switch, in case of a table miss (absence of flow entry) it may get forwarded to the controller, which determines the next course of action for the respective traffic flow. A schematic representing generic controller architecture is given in Fig.2.7. Depending on the deployed redundancy measures, switches may communicate with either a single or several controllers [34]. Inter-controller communication is usually served by an external legacy protocol such as the Border Gateway Protocol (BGP) or the Session Initiation Protocol (SIP) over TCP channels to exchange routing information. Multiple controllers can improve the reliability of the system. In case of failure of one controller or control channel, the switch can obtain flow forwarding instructions from another controller instance. The number of controllers and their placement depends on the topology and operational requirements of an organization. Two popular schemes proposed include the vertical approach, where multiple controllers are in effect controlled

by controller(s) at a higher layer, and the horizontal approach in which controllers establish a peer-to-peer communication relationship [65][67].

Controllers are usually hosted on network attached server(s). In the case of multiple controllers, OpenFlow dictates that the switches maintain a control channel with each controller, independent of the data channel. A summary of commonly used OpenFlow compliant controllers is given in Table 2.4, along with their development platform and brief description. The development of controllers has been rather organic due to the ongoing development of the SDN area. The two broad categories of controllers covered in the Table 2.4. include general and special purpose controllers. NOX and POX were early stage general purpose controller platforms during SDN evolution[68][69]; POX in addition to offering OpenFlow support also offers a visual topology manager. Ryu, developed in Python by the NTT Corporation, has found increased applicability in several research studies, being a complete SDN ecosystem supporting the OpenFlow protocol as well as the RESTful at the northbound interface [70]. The OpenDaylight (ODL) controller platform founded and led by several industry giants offers Java based development and deployment of carrier-grade SDN solutions [71]. Special purpose controllers such as FlowVisor [72], RouteFlow [73] and Oflops [74] serve specific tasks including serving as transparent proxies between switches and multiple controllers, performing virtualized IP routing over OpenFlow network switches and benchmarking switch performance.

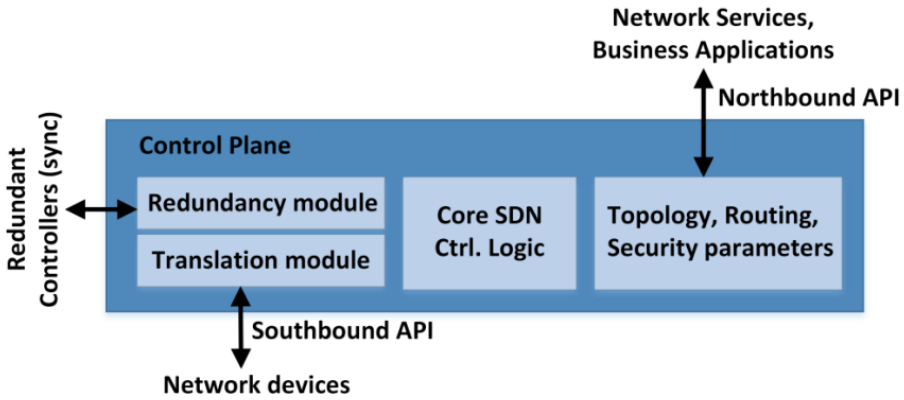


Figure 2.7. SDN Controller Schematic

Table 2.4. Popular OpenFlow Compliant Controller Implementations

Controller	Implementation	Open Source	Developer	Description
NOX	C++/ Python	Yes	Nicira	The first OpenFlow controller [68].
POX	Python	Yes	Nicira	Controller supporting OpenFlow having a high-level API including topology graph and virtualization support [69].
Ryu	Python	Yes	NTT, OSRG	Network Operating System (NOS) that supports OpenFlow [70].
OpenDaylight	Java	Yes	Industry consortia	Platform for building programmable, software-defined network applications [71].
Beacon	Java	Yes	Stanford University	Java-based controller that supports both event-based and threaded operations [75].
Floodlight	Java	Yes	Big Switch	OpenFlow controller, forked from the Beacon controller [76].
Helios		No	NEC	Controller providing shell environment for integrating experiments [77].
Trema	C/ Ruby	Yes	NEC	Full-stack framework for developing OpenFlow controllers in Ruby and C [78].
Jaxon	Java	Yes	Independent	NOX-dependent Java-based OpenFlow controller [79].
MUL	C	Yes	Kulcloud	OpenFlow controller having multi-threaded infrastructure at its core and designed for performance and reliability in mission-critical environments [80]..
IRIS	Java	Yes	IRIS Team - ETRI	OpenFlow Controller having horizontal scalability for carrier-grade network, high availability and multi-domain support [81].
Maestro	Java	Yes	Rice University	OpenFlow operating system for orchestrating network control applications [82]..
NodeFlow	JavaScript	Yes	Independent	OpenFlow controller written in pure JavaScript [83].
NDDI - OESS	C++	Yes	Internet2, Indiana University	Application to configure and control OpenFlow enabled switches through a simple and user friendly interface [84].
RouteFlow	C++	Yes	CPqD	*Special purpose* provides virtualized IP routing composed of an OpenFlow controller application, an independent server and physical network emulation [73].
FlowVisor	Java	Yes	Stanford University/ Nicira	*Special purpose* OpenFlow controller, a transparent proxy between switches and multiple controllers [72].
SNAC	C++	No	Nicira	*Special purpose* controller built on NOX uses a web-based policy manager [85].
Resonance	NOX+OpenFlow	Yes	Georgia Tech.	*Special purpose* network access control application built using NOX and OpenFlow
Oflops	C	Yes	Cambridge, Berlin, Big Switch	*Special purpose* standalone controller used to benchmark performance and test an OpenFlow switch [74].
ovs-controller	C	Yes	Independent	Reference controller packaged with Open vSwitch [86].

2.5.2 SDN compliant switches

In addition to the several network controllers on offer, several types of SDN software and hardware switches are currently available. A summary of current OpenFlow switch implementations are presented in Table 2.5, along with their brief description and development platform (language). The software switches can be used to run SDN test simulations as well as develop protocols and services. Open vSwitch for example, is now a part of the Linux kernel (as of version 3.3) and facilitates both the ability to serve as virtual gateway between physical and virtual services as well as a testing platform to be used in tandem with SDN topology simulation tools such as Mininet [103]. In addition to software switches, companies such as IBM, HP and NEC have also brought physical carrier-grade switches to market. The networking industry has taken keen interest in SDN evidenced by the availability of a number of commercial hardware switches which are OpenFlow-enabled.

2.6 Simulation, development and debugging tools

The development of SDN has seen the advent of several key simulation and emulation test-beds to carry out feasibility studies and introduce new protocols and services. The set of tools available for the purpose can be broadly divided into three categories (i) simulation and emulation platforms (ii) software switch implementations and (iii) debugging and troubleshooting tools. A summary description of major utilities within each category and their description are given in Table 2.6. An overview of the tools is given below.

2.6.1 Simulation and debugging platforms

a) **Mininet:** Among the emulation tools, Mininet [103] is the most prominent. The platform allows an entire network based on OpenFlow to be emulated on a single hosted machine. Mininet simplifies the development and deployment of new services by providing a software platform to create virtual machines, hosts and network switches connected to an in-built (ovs-reference) or user-defined controller for testing purposes. The latest Mininet v2.2.1 supports OpenFlow versions up to 1.3 (along with Open vSwitch v2.3). While Mininet supports Open vSwitch [86] by default, it can also be customized to use an external user space switch such as the softswitch13 [90].

Table 2.5. Common OpenFlow Compliant Switches and Standalone Stacks

Switch	Implementation	Category	Description
Open vSwitch	C/ Python	Software	OpenFlow stack that is used both as a virtual switch and ported to multiple hardware platforms [86].
Indigo	C	Software	Software running on hardware switching implementations and based on the Stanford reference [87].
OpenFlowJ	Java	Software	OpenFlow stack written in Java [88].
OpenFaucet	Python	Software	Python implementation of the OpenFlow 1.0 protocol [89].
ofsoftswitch13	C/ C++	Software	User-space software switches implementation [90].
Pantou	C	Software	OpenFlow port to the OpenWRT wireless environment [91].
Oflib-node	JavaScript	Software	OpenFlow protocol library for Node.js converting between the protocol messages and JavaScript objects [92].
OpenFlow Reference	C	Software	Minimal OpenFlow reference stack that tracks the specification [17].
Open Source Network Operating System (ONOS)	Java	Software	Open source scalable control plane cluster offering GUI and OpenFlow as well as NetCONF support [93].
Pica8	C	Physical and software	Software platform for hardware switching chips which includes L2/L3 stack [94].
A10 Networks –AX Series	Proprietary	Physical and software	Physical and software appliances (AX Series), offering L4-7 programming [95].
Big Switch Networks - Big Virtual Switch	Proprietary	Physical and software	Data center network virtualization application built upon an OpenFlow switches [96].
Brocade ADX Series	Proprietary	Physical and software	Secure and scalable application service infrastructures using the RESTful API on northbound interface [97].
NEC ProgrammableFlow Switch Series	Proprietary	Physical and software	Series offers network virtualization, multipath routing, security, and programmability [98].
ADVA Optical - FSP 150 & 3000	Proprietary	Physical	FSP 150 carrier Ethernet and FSP 3000 transport layer products [99].
IBM RackSwitch G8264	Proprietary	Physical	Offers low cost flexible connectivity for high-speed server and storage devices in DC environments [100].
HP 2920, 3500, 3800, 5400 series	Proprietary	Physical	Advanced modular switch series built on programmable ASICs offering scalable QoS and security [101].
Juniper Junos MX, EX, QFX Series	Proprietary	Physical	Series supports different versions of OpenFlow varying with model [102].

b) **NS-3:** The network simulator has long been used by the networking community to test and develop networking protocols and services. The latest ns-3 simulator offers support for OpenFlow switches, however, it is limited to a very early version of OpenFlow v0.89 [104]. While official work is continuing on introducing newer updated versions of OpenFlow, a specialist OpenFlow 1.3 module for ns-3 namely OFSwitch13 module has been designed independently [105]. The module relies on the ofsoftswitch13 library providing a data path (switch) implementation in the user pace and to convert OpenFlow v1.3 messages from wire format.

c) **OMNeT++:** The OMNet++ is a discrete event simulator allowing the development and testing of SDN based network models [106]. SDN oriented projects can be integrated with OMNeT++ using an OpenFlow components and an INET Framework.

2.6.2 Software switch implementations

A non-exhaustive summary of software switches which are also used for experimentation and new service development were given earlier in Table 2.5. Well-adopted implementations such as the Open vSwitch have been implemented in multiple platforms including Mininet and ns-3. A brief overview of some of the well-known software switches presently available is given below.

a) Open vSwitch: The Open vSwitch is one of the most widely deployed software switches. It employs an OpenFlow stack that can be used both as a virtual switch in virtualized network topologies and has also been ported to multiple hardware/ commodity switch platforms. [86] The Open vSwitch has been built in the Linux kernel since version 3.3 [17].

b) ofsoftswitch13: The ofsoftswitch13 running in the user space also provides support for multiple OpenFlow versions [90]. The soft switch supports Data Path Control (Dpctl), a management utility to directly control the OpenFlow switch, allowing the addition and deletion of flows, query switch statistics and modify flow table configurations. Although ofsoftswitch13 supports a variety of OpenFlow features, it has recently run into some compatibility issues with latest versions of Linux (Ubuntu 14.0 and beyond) and developer support has also stagnated.

Table 2.6. Common OpenFlow Compliant Utilities

Category	Purpose	Software and tools
Emulation and simulation	Emulating network topologies as well as providing a reference for network event simulation	Mininet [103], ns-3 [104], OMNeT++ [106]
Software switches and platforms	A software platform to test and validate switch-controller behaviour and southbound protocol working	Open vSwitch [86], ofsoftswitch13 [90], Indigo [87], Pica8 PicOS [94], ONOS [93], Pantou [91]
Debugging and troubleshooting	Specialist tool set to debug SDN behaviour at the switch and controller level	STS [107], Open vSwitch [86], NICE [108], OFTest [109], Anteater [110], VeriFlow [111], OFRewind [112], NDB [113], Wireshark [114]

c) Indigo: The Indigo project is an open source implementation of OpenFlow which can be run on a range of physical switches and utilizes the hardware features of existing Ethernet switch ASICs to run OpenFlow pipeline at line rates [87]. The implementation is based on the original OpenFlow Reference Implementation and currently supports all features required in the OpenFlow 1.0 standard.

d) Pica8 PicOS: The PicOS by Pica8 is a network operating system allowing network administrators to build flexible and programmable networks using white box switches with OpenFlow [94]. The proprietary software allows the integration of OpenFlow rules to be used in legacy layer 2 / layer 3 networks, without disrupting existing network and creating a new one from scratch.

d) Open source network operating system (ONOS): Although not specifically a soft switch implementation, the mission of ONOS is to develop an operating system resilient for carrier-grade deployment of software defined networks [93]. The ONOS GUI provides the multi-layer view of the underlying network and allows operators to peruse network devices, links, and errors.

e) Pantou: Pantou modifies a commercial wireless router and access point to an OpenFlow enabled switch. The OpenFlow protocol is implemented as an application on top of OpenWRT platform [91]. The OpenWRT platform used is based on the BackFire release (Linux v2.6.32) while the OpenFlow module is based on the Stanford reference implementation in user space.

2.6.3 Debugging and troubleshooting tools

Debugging and troubleshooting tools serve as vital resources for development and testing of SDN based services. The following list presents some of the popular SDN debugging and verification tools.

a) **SDN troubleshooting system (STS):** STS simulates the network devices of your network while also allowing enough programmatically to generate and examine various test case deployments. Users can interactively visualize the network states, the real-time changes and also automatically determine the events that trigger deviant behaviour and identify bugs. The implementation is based on the POX controller platform, with the feasibility to use other OpenFlow compliant controllers supporting OpenFlow v1.0.

b) **Open vSwitch specific tools:** The Open vSwitch comes with a comprehensive set of tools to debug the switch and network behaviour. The utilities comprise of the following:

- ovs-vsctl: Used for configuring the switch (daemon) configuration database (known as ovs-db.)
- ovs-ofctl: A command line tool for monitoring and administering OpenFlow switches.
- ovs-dpctl: Used to administer Open vSwitch datapaths (switches). In addition to Open vSwitch ovs-dpctl, a reference dpctl comes with the OpenFlow reference distribution and enables visibility and control over a single switch's flow table. The syntax of commands used by the utilities is quite different.
- ovs−appctl: Used for querying and controlling Open vSwitch daemons.

c) **NICE:** NICE offers an automated testing tool used to identify and check bugs in OpenFlow programs [108]. The tool applies model checking to explore the entire state of the controller, the switches, and the hosts. To address scalability issues, the tool uses model checking with symbolic execution of event handlers (identifying the representative packets that exercise code paths on the controller). NICE prototype tests Python applications using the NOX platform.

d) **OFTest:** OFTest is an OpenFlow switch test framework built in Python and also includes a collection of test cases [109]. The tool is based on the *unittest* function, which is included in the standard Python distribution. OFTest hosts the switch under test and the OFTest code runs on the test switch. Both control plane and data plane side of switch connections can be tested by sending and receiving packets to the switch as well as polling switch counters.

e) **Anteater:** Anteater attempts to check network invariants that exist in the networking devices, such as connectivity or consistency [110]. The main benefit of using Anteater is that it is agnostic to protocols and will catch errors that result from faulty firmware as well as control channel communication.

f) **VeriFlow:** VeriFlow allows real-time verification and resides between the controller and the data plane elements (switches) [111]. The framework allows pruning of flow rules that may result in anomalous network behaviour.

g) **OFRewind:** OFRewind is another tool that allows debugging of network events both in the control and data plane and to log these at different levels of detail to be replayed later in examining problematic scenarios and localize troubleshooting efforts [112].

h) **Network debugger (NDB):** NDB implements traffic breakpoints and packet-backtraces for an SDN environment [113]. Similar to the popular software debugging utility gdb, users can isolate networking events that may have led to an error during traffic forwarding. It works using the OpenFlow API to configure switches and generate debugging events. NDB then acts as a proxy intercepting OpenFlow messages between switches and the controller. The debugger relies on OpenFaucet python module implementing OpenFlow v1.0.

i) **Wireshark:** The popular network analyser Wireshark can be deployed on the controller or Mininet host to view OpenFlow exchange messages between the controller and individual switches. The OpenFlow dissector is available in the current Wireshark release [114]. OpenFlow control packets can be directly filtered while capturing using the TCP control channel traffic ports (6633 and 6653). The

captured packets provide a useful learning tool to understand switch-controller behaviour.

2.7 SDN applications

Software-defined networking has found a great deal of applicability in a wide range of networking avenues. Real-time programmability through the centralized controller has presented opportunities in data center networking, large campus environments as well as experimental designs focusing on enhancing end user experience and making residential networks more manageable. Furthermore, mobile operators have also shown keen enthusiasm in bringing the technology to 5G/ LTE mobile networks to allow simplified yet rapid development and deployment of new services. Some of the key applications of SDN are highlighted as follows.

2.7.1 Data centers and cloud environments

Optimal traffic engineering, network control, and policy implementation are absolute requirements when operating at large scales, as is the case for data centers. Increased latency, faults and prolonged troubleshooting may result not only in negative end user experience but significant cost penalties for operators. Data center (DC) SDN implementations, therefore, using a centralized control framework monitor and manage hundreds of network devices and services promising effective resource provisioning for operators. Google for example, has used SDN technology to connect its geographically dispersed data centers around the globe, allowing increased resilience and manageability [38].

Cloud computing has also seen the integration of SDN based traffic engineering solutions to increase service scalability and automated network provisioning. A notable example is the Microsoft public cloud [201]. The study highlights SDN based load balancing solution Ananta, a layer 4 load balancer employing commodity hardware to provided multitenant cloud management. Using host agents, packet modification is localized enabling high scalability across the DC. The project has seen a significant level of deployment in the Microsoft Azure public cloud, allowing high throughput for several tenants allocated a single public IP address. Another SDN deployment in cloud environment is NTT's software-defined edge gateway automation system [314]. The gateway uses OpenFlow protocol for maximum flexibility in network provisioning and evaluates possible

extension to existing OpenFlow features, baselining the SDN stack to allow robust cloud gateway deployment.

On a slightly separate strand, reducing energy consumption in data centers has also been an area of focus for operators to reduce operational costs. Since most DCs are overprovisioned for peak traffic, the energy efficiency during periods of underutilization is minimal. SDN technologies such as ElasticTree allow network wide power management by switching off redundant switches from the controller side during low traffic demand [39]. DC network environments to-date remains one of the primary beneficiaries of the SDN framework.

2.7.2 Campus and high speed networks

Enterprise networks may show a great deal of variability in traffic patterns requiring proactive management to adjust network policies and fine tune performance using a programmable SDN framework. A centralized control plane may also aid in effective monitoring and utilization of network resources for re-adjustment. An additional benefit may be to eliminate middle boxes providing services such as NAT, firewalls, access control and service differentiation solutions and load balancers [41-43]. With increasing use of fibre technologies in enterprise networks, the Optical Transport Working Group (OTWG) created by the Open Network Foundation (ONF) envisions applying southbound protocols such as OpenFlow to improve optical network management flexibility. Inclusion of an SDN controller for optimal network provisioning, while offering simplicity, also allows external third-party network administration of the enterprise network and added support for visualization [44].

The integration of heterogeneous networking technologies using OpenFlow enabled network elements and a centralized controller has seen a great deal of applicability in optical high-speed networking. High speed optical communications require an appreciation of the existing OpenFlow framework and possible extensions to achieve a higher level of integration [316]. Using centralized real-time programmability, SDN enabled hardware from multiple vendors and optical packet based as well as circuit-switched networks can be placed under the SDN controller. Gudla et. al [315], for example used NetFPGA [16] along with Wavelength Selective Switching (WSS) for packet and circuit switching facilitated using the OpenFlow protocol. Liu et. al. [317] used virtual Ethernet based interfaces to demonstrate OpenFlow based wavelength path controlling in optical networking. A commodity SDN controller such as NOX, POX, etc., can operate the optical light paths using OpenFlow by mapping virtual Ethernet interfaces to physical ports of an optical cross-connect node.

The evaluation of network performance metrics included in the study detailed promising results in reducing latency of path setup and verification of routing and wavelength assignment allocation using dynamic node control providing paving the way for future software defined optical networking (SODN). In comparison with the typical distributed GMPLS protocol, SDON using a unified control protocol for QoS metrics offers greater capacity and performance optimization in optical burst switching [318]. The application of SDN, and in particular OpenFlow based controls in high speed and campus networking, therefore, continues to grow resulting in new as well as hybrid solutions to achieve greater network programmability.

2.7.3 Residential networks

Software defined networking has also been considered as an efficient means to manage residential and small office home office networks. Management of residential networks presents a key challenge for residential users and service providers alike, including the benchmarking of home user activities through collection of traffic metrics and the setup involved. One of the fundamental benefit of such networks is that operators and residential users are provided with a greater degree of visibility into network usage through effective monitoring using the SDN framework [45-47]. To relieve the burden of network management on residential gateways, Dillon and Winters [49] proposed the introduction of virtual residential gateways (data plane) using software defined networking controller(s) at the service provider side to allow providers remote management flexibility as well as innovative service delivery to homes. The residential router or gateway may be controlled and managed remotely via an SDN controller at the service provider premises, with the latter being responsible for fine tuning and troubleshooting the residential network [46][48-50]. Some contrasting schemes propose giving users more control and incorporating SDN based monitoring in the residential environment to change network policies [49][51][52].

From a security perspective, it has been argued that an SDN based anomaly detection system in a residential SDN environment provides more accuracy and higher scalability than intrusion detection systems deployed at Internet service provider side [48]. Feamster in [46], proposed completely outsourcing residential network security utilizing programmable network switches at the customer premises to allow remote management. By employing the outsourced technical expertise, management and running of tasks such as software updates and updating anti-virus utilities may be done more effectively as the external operator also has a wider view of network activity and emerging threat vectors. The privacy of end users where technical operations related to residential network management are outsourced also requires consideration [47]. The inclusion of SDN

framework in residential networking, given its benefits to end users, remains an active area of academic and industry research.

2.7.4 Wireless communications

Due to the real-time programmability and potential to seamlessly introduce new services and applications to consumers, the SDN paradigm has also been ported to mobile communication networks. A programmable wireless data plane, offering flexible physical and MAC address based routing in comparison to the layer 3 logical address based traffic forwarding, allowed developers to fine tune mobile communications performance [53][56]. Using the control plane, user traffic can be segregated and routed over different protocols such as WiMAX, 3GPP or advanced LTE.

Furthermore, there have been growing efforts to include the SDN layering model in the upcoming 5G mobile communications realm and move from a flat topology, which increasingly relies on the core, to a more modular control and traffic forwarding framework. Similar to information-centric networking, data may be cached locally at certain points within the 5G network, as coordinated by the SDN controller, to reduce latency in service delivery to end users [54-55].

Finally, within 5G networks, efficient resource management is essential to allow maximum utilization, network slicing, and guaranteeing fairness among several QoS classes [319]. Using SDN to maximize energy efficiency in 5G networking has, therefore, been the subject of investigation in several studies. SDN has also been test-implemented in 5G to allow rapid application service provisioning while adhering to stringent QoS requirements. At the more local level such as Wi-Fi access networks, SDN could be used to offer a great deal of ubiquity in connecting to different wireless infrastructures belonging to different providers using user device identity management which is in turn coordinated and proactively managed by the SDN controller [57].

2.8 Research challenges

Increasing application of SDN framework in several network settings have also highlighted areas of concern ranging from application performance to security inadequacies inherent in the present architecture, briefly detailed in chapter 1. The present section discusses the major investigations and research advances made in several SDN areas in detail. A summary of the key areas of research and subsequent initiatives in software defined networking is presented in Table 2.7.

2.8.1 Controller scalability and placement

The SDN controller is responsible for managing data plane switches and providing traffic forwarding rules that affect individual packet behaviour. In larger network environments, the placement of the SDN controller is highly pertinent in achieving optimized network connectivity [135]. The connections between controller(s) and switches in the data plane require low latency for seamless operation [136]. To address scalability concerns, having more than one controller serving the data plane are, therefore, usually required. In critical network infrastructures, multiple controllers, may also be required in order to offer a greater level of redundancy. Prevalent research in this area seeks to deploy multiple controllers in several network locations and consequentially determining the exact point of controller placement is critical [135-139].

The controller placement problem was first identified by Heller et. al. in [136] as an NP-hard problem focusing on the determination of exact number and optimal location for SDN controllers. The study highlighted that the best controller placement solution should minimize the controller to switch control traffic latency. Similarly, Sallahi et. al. [137] considered the placement problem from an operational perspective discussing the cost involved in deploying and installing controllers and connecting these to the wider network fabric. Both studies used traversal search algorithms perusing through the best solutions to find an optimal candidate, a time consuming process proportional to the size of the network. Some of the topologies took an order of magnitude greater than 30 hours to find a satisfactory placement solution. From a controller workload standpoint, Yao et. al. [138] highlighted the fact that the placement solution should also consider the workload for each controller and that it does not exceed controller capacity. The proposed placement solution used k-center algorithm [140] to minimize the value of k (controllers) that meet the workload and capacity requirements. In a similar work, Yao et. al. [141], discussed placing controllers at network hotspots where switches carry most of the traffic. The switches in the proposed solution may utilize less overloaded controllers, migrating from one to another with changing traffic demand.

Ros et. al [142] focused on network reliability, highlighting a positive correlation between fault tolerance and controller placement. The study used heuristic algorithms to compute controller placement and the maximum number of controllers which may be deployed to meet network reliability. Zhang et. al [135] used the min-cut method discussed in [143] to separate the network into smaller networks, each having its own controller. Similarly Guo et. al. [144] generated a hierarchical tree [145] of network nodes, dividing it into k clusters or subnetworks. Nodes with maximum closeness to other nodes were selected for controller deployment. In [146], a greedy

Table 2.7. Summary of SDN Research Initiatives

Area of concentration	Brief description	Research initiatives
Controller scalability and placement	Controller placement in large SDN environments offers a complexity optimization problem affecting latency, capacity and fault tolerance. The design of the control plane remains a multi-faceted topic of several research studies.	• *Reducing latency* by solving optimal controller placement problem (NP-hard). • Solutions *minimizing controller workload* with respect to controller placement. • Placement schemes offering *greater reliability* using heuristic and greedy algorithms to refactor larger network into smaller (separate controller) sub-networks. • *Combinatorial approaches* optimizing multiple network performance metrics in relation to controller placement, providing a trade-off between performance gains and operational requirements. • *Distributed control architectures* considering hierarchical controller clusters to address scalability issues.
Switch and controller design	Studies aimed at improving northbound API standardization among multiple application platforms, level of control delegation appropriate for data plane elements and optimal hardware architectures.	• *Standardization of the northbound API*, involving studies in designing a policy abstraction language compatible with several platforms and offering vertical and horizontal integration with parallel services and underlying network fabric. • Greater level of *control delegation* to network switches aimed at reducing controller overhead and increasing fail-safe redundancy. • *New architectures* for controller and switch design.
Security	SDN due to centralized network control creates potential security challenges directed at control plane (traffic) and data plane elements including network appliances and middle boxes.	• Designing SDN security reference models focusing on securing the control plane to avoid network disruption and security compromise. • Control channel and application-controller traffic monitoring and anomaly detection. • Network /state information storage and retrieval for post-even and forensic examination.
Application performance	Improving the performance of individual network applications and services in the SDN framework using novel optimization techniques in wired, wireless and heterogeneous settings.	• Increasing SDN *application-awareness* and *optimizing time-critical application* services using flow metering. • Development of SDN *monitoring tools* for evaluating performance gains in heterogeneous network environments. • *Embedding network services* such as authentication, firewalls, proxies, etc. in the data plane fabric. • *Information-centric* approaches exploiting location-based data caching.

algorithm was used to enhance controller placement reliability in the event of network state changes as well as single link failures in tandem with the optimal controller placement. Hu et. al [147] used multiple algorithms including l-w greedy, and simulated annealing and brute force searching with brute force offering the best optimal solution.

Other notable works such as Onix [65], HyperFlow [66] and Kandoo [67] propose a distributed control architecture allowing a significant level of scalability and reliability in large SDNs. HyperFlow details a flat or horizontal scaling of controllers, while Kandoo and Onix use a hierarchical structure. The schemes allow multiple controllers to manage the data plane. The distributed architecture comprises of root and localized controllers each control-level having a different view of the underlying network. Another category of distributed controller design includes Difane [148] and DevoFlow [149] which delegate some control functions to the SDN switches to reduce the controller overhead. Offloading workload helps in improving network scalability, however, requires significant modifications in switching hardware to accommodate functional requirements. SDN controller placement, therefore, remains an active area of research with several solutions and approaches pursued to achieve a greater deal of scalability allowing greater network performance.

2.8.2 Switch and controller design

Innovations and proposals in controller and switch design seek to circumvent some of the problems associated with policy implementation while simultaneously addressing additional areas needing improvement including controller and switch scalability. Although controller-switch interaction is served by standard southbound APIs such as OpenFlow [17], XMPP [20] or ForCES [8], as mentioned earlier, a similar level of standardization is not available at the application-controller northbound interface. Since the northbound interface purely relies on the application logic, the supporters of non-standardization (of northbound API) argue that the present framework allows for greater degree of innovation with custom northbound communication fitting the application or service using the SDN. A number of controller utilities and platforms described earlier in the chapter allow applications to interact with each other as well as the underlying network elements for traffic engineering purposes. The application developer, however, needs an in-depth knowledge of the controller implementation to deploy application APIs.

A few proposals have highlighted the need for network configuration language that can seamlessly express the administrator policies seamlessly on the underlying controller implementation [150-153]. Policy description language such as Procera [150] and Frenetic [151] build a policy layer on

existing controllers, interfacing with configuration, graphical interfaces and other network monitors to translate administrator defined policies to flow level details which can be used by the controller. Other examples exploring network configuration languages include FML [152] and Nettle [153]. Feamster and Kim [107], propose using policy definitions for network configuration and management according to changing network conditions. The northbound communication API may be further used in such cases to allow the SDN to apply segregated policies on same application flows based on destination or source IP address. Monsanto et. al [154] on the other hand introduce the concept of modularized policy implementation which ensures that flow rules for one network application task do not interfere or replace rules for other tasks. As mentioned earlier, the chances of ONF or the industry standardizing the northbound API look slim and operators will continue to develop and deploy custom Pro-active implementation of policies in the switches lead to a substantial lowering of control overhead generated during real-time operation [148][149].

In terms of switch design innovation, Luo et. al [156] discuss the replacement of ASIC based counters for rule-matching in switches to ones processed in the CPU. Other technologies such as FLARE [155] allow for complete programmability of not only the data and control planes but also the control channel between them. A single controller may be able to handle up to 6 million to 12 million flows per second [157][75]. However, lowering propagation latency and increasing fault-tolerance and robustness also requires controller architectures using horizontal and hierarchical clusters [65-67].

2.8.3 Security

The increasing interest in SDN in the networking community also initiated a significant debate highlighting the inherent security challenges of an SDN framework. The OpenFlow switch specification [86] includes relatively basic security incorporation in SDNs using optional transport layer security (TLS) allowing mutual controller-switch authentication without specifying the exact TLS standard. TLS although, has not been given much thought in Several open source controller and switch platforms, however, have not implemented TLS, which may lead to anomalous rule insertion in flow tables [299]. Centralized control makes the scheme vulnerable to attacks directed at the control plane which may disrupt the entire network. The intelligence in the centralized control plane may offer hackers the opportunity to explore security vulnerabilities in the controller and take over the entire network [64][158]. On the positive side, it is argued that the information generated from traffic analysis or anomaly detection in the network can be regularly transferred to

the SDN controller, having a global network-wide view to analyse and correlate feedback for efficient security [307].

In addition to securing the controller, targeted attacks on the network (e.g. DDoS) and subsequent controller failure may result in substantial network service downtime until the controller is up and running and the threat has been mitigated. The control channel between the controller and network devices has to be secure enough to reject anomalous injection; the same is true for application-controller communication. Effectively establishing trust among all the network devices and the applications on top are considered a key security concern. Vulnerability analysis, mitigation studies and a standardized framework for SDN security has therefore, been the focus of multiple deliberations [308-311] with a great deal of focus in the security domain laid on controller-switch and inter-controller communication. Shin and Gu [308] for example, undertake vulnerability evaluation of SDN by evaluating the feasibility of fingerprinting attacks. The study fingerprinted the SDN equipment such as OpenFlow switches and targeted the respective elements with denial of service (DoS) attack on the controller via control channel and on the data plane elements by exploiting flow tables. Both entities are identified as significant areas of SDN vulnerability. Similarly, Smeliansky [309] discussed communication protocol security with consideration for infrastructure and software services, concluding that control-data plane and control to control plane communication requires substantial hardening to mitigate security threats. Some of the solutions in controller-switch communication challenges propose replication of SDN controllers and network applications to provide redundancy and fail-safe operations, which may arise due to misconfigurations and software bugs [312]. Other investigations propose service mobility, to counter security threats [299]. The controller functionality for example, could be continuously shifted across several network elements making targeted attacks on the controller more challenging for those seeking to exploit the control-plane.

SDN security has also been the subject of work in particular avenues including wireless communications and cloud computing, for the technology to gain wider acceptance in [310][311][313]. Schehlmann et. al in [310] discuss potential improvements in network management costs, as well as attack detection and mitigation by using SDN framework itself as a potential barrier to security vulnerabilities. SDN enables the incorporation of certain security functionalities through decoupling of network control from forwarding logic where traffic filtering can be achieved using key traffic (packet) identifiers usually requiring dedicated firewalls and intrusion detection/ preventions systems in legacy networking. Additional security layers may be

added on top of existing SDN layers as well as by the introduction of agents in data plane elements to incorporate granular traffic filtering in heterogeneous wireless networks [311]. Security approaches may focus on securing the network itself by embedding intelligent security alarms in the network elements such as switches and controllers or include SDN oriented security utilities in the functional entities such as application servers and storage clusters. Similarly, in SDN-enabled cloud computing, additional security may be introduced at each SDN layer based on underlying operational requirements to make intra and inter-cloud communication more secure [313].

In addition to specific application avenues real-time SDN monitoring has to be robust enough to offer timely detection of anomalous network events and containment [48]. The monitoring information not only provides insight into traffic but quite similar to the case of legacy network systems, may also have enough storage capacity system to satisfy technical (forensic) as well as legal requirements [43]. Organizations such as OpenFlowSec [159] focus on security challenges presented by the SDN paradigm and OpenFlow enabled devices. Development work has considered designing reference implementations of security features at different layers of the OpenFlow stack. A detailed taxonomy of security threats in the SDN paradigm is presented in [160]. Beyond the basic SDN architecture, the deployment of robust security in the SDN paradigm is still very much an area requiring further study. It is however, a widely held belief that without a significant increase in focus on SDN security, the paradigm may not see adoption beyond private DC infrastructures or autonomous organizational deployments.

2.8.4 Application performance

Application performance improvement has been the primary area of focus in a number of SDN related studies ranging from application-aware SDNs, utilizing the framework for optimizing time-critical applications to the development of novel application performance monitoring solutions. The following sub-sections discuss the studies carried out in this regard.

a) Application-awareness in SDN

Traffic optimization carried out on the basis of network applications to a significant extent focuses on increasing specific service performance(s) in SDN. Supporters of ‘application-aware’ SDN infrastructure consider the benefits the framework brings in offering enhanced performance for specific applications. While southbound APIs such as OpenFlow are capable of Layer-2/3/4 based policy enforcement they lack high level application awareness and are mainly responsible for

configuring the underlying network elements. Network management primitives are, therefore, employed which customize traffic forwarding policies for individual applications and the SDN controller translates these into device configuration using a southbound API such as OpenFlow. The concentration in this domain has seen several studies particularly concentrating on video streaming (IPTV, YouTube, P2P video, etc.) and voice communications (VoIP), using the SDN architecture to improve the respective application quality of service. Qazi et. al [60] in one such 'application-aware' SDN work discuss Atlas, a crowd sourcing approach which deploys software agent on user devices and collects the netstat logs, in turn exported to the SDN control plane. Using the exported logs in tandem with machine learning classification the scheme identifies approximately forty applications (from Google Play Store). The SDN controller in turn applies pre-defined policy actions to the respective flows as well as collects flow statistics per application for monitoring purposes. Mekky et. al [115] proposes a similar per application flow metering approach using the SDN framework. Applications are identified in the data plane and the relevant policies applied using individual application tables. The proposed scheme minimizes SDN control channel overhead. The study showed significantly good application forwarding performance with low overhead when tested and implemented using a content-aware server selection application along with multiple virtual IP pool of services.

b) Video streaming and real-time communication

Focusing on video streaming applications, Egilmez et. al [116], devised an analytical framework for traffic optimization at the control layer offering dynamic and enhanced Quality of Service (QoS). The study reported significant improvement for streaming of encoded videos under several coding configurations and congestion scenarios. Jarschel et. al [61] instead focused specifically on improving YouTube streaming experience for end users. The study used Deep Packet Inspection (DPI) and demonstrated how application detection along with application state information can be used to enhance Quality of Experience (QoE) and improve resource management in SDN. Ruckert et. al [117] developed Rent a Super Peer (RASP), a peer-to-peer (P2P) streaming mechanism using the OpenFlow network. RASP employs a cross-layered approach, allowing service providers to facilitate P2P based live video streaming over two OpenFlow-based service components: a network proxy application and software defined multicast (SDM) application, while the controller is responsible for integrating components and providing an interface to RASP functionality. The proposed methodology results in efficient delivery of P2P video streaming traffic to be used in future service provider networks. Another example of video streaming optimization is the CastFlow [118] which

proposes a prototype aimed at decreasing latency for IPTV using a multicast approach, logically centralized and based on OpenFlow networks. During multicast group setup all possible routes are calculated in advance to reduce the delay in processing multicast group events (joining and leaving hosts and source changes). Using Mininet based emulation the reported results showed satisfactory performance gains and the time to process group events appeared to be greatly reduced. Noghani and Sunay [119], also utilize the SDN framework in allowing the controller to not only forward IP multicast between the video streaming source and destination subscribers but also manage the distributed set of sources where multiple description coded (MDC) video is available. For medium to heavy loads, the SDN based streaming multicast framework resulted in enhanced quality of received videos. Some related studies seek to substantiate the importance that the underlying test-beds may have on any evaluations reporting perceived improvements in video streaming quality using SDN. Panwaree et. al in [120], for example, benchmark the packet delay and latency performance of videos tested on Mininet as well as actual physical PC clusters using Open vSwitch. It was noted that the packet delay and loss in the PC-cluster testbed was higher than the Mininet-emulated testbed suggesting careful interpretation of performance expectations in realistic environments.

In terms of industry efforts in promoting application performance using SDN, the Microsoft Lync platform [62] offers a prominent test case example of an application using SDN based network abstraction to optimize real-time messaging, video and voice communication among Lync clients. Microsoft released a purpose built Lync northbound API for SDN that gives administrators visibility in to voice, video and media stream metrics deployed in enterprise environments. Lync SDN API, as per Microsoft can immediately enhance the diagnostic capability of monitoring Lync communication in SDN as well improve QoS. The effects of Lync and other similar targeted specific service improvement on other applications in the enterprise network and the resulting overall experience of end users remains to be considered.

c) Information-centric application delivery models

Another category of work in application performance improvement proposes an information-centric approach for achieving optimized service delivery in software defined networking. The motivation behind the studies is the fact that while the present Internet usually exploits location-based addressing and uses host to host communications, addressing of data by name (Named Data Networking) and distribution over dispersed locations may offer enhanced application content

delivery to end users. Information-centric content delivery mechanisms may then be combined with SDN to allow greater deal of network programmability and serve as a key enabler for content distribution. Studies including [125-130] propose the use of SDN and OpenFlow protocol to support customized matching of packet headers for service delivery to end users from content servers with significant performance gains.

d) Data center solutions

Traffic measurements in data centers, however, show signification variation in network workload hosting multiple applications on the same physical or virtual network fabric [5]. The SDN paradigm as mentioned in the earlier in section 2.7.1, brings automation and on-demand resource allocation in data center networking [1][2]. Using SDN, the DC environment can afford faster state changes, a fundamental necessity of modern data centers [38][286]. Several prior works have discussed the improvement of individual applications and services in the DC network environment. Application connectivity models were used in [289] and [21] to allocate per-application network bandwidth. However, application delivery constraints are prevalent in data centers where virtual machines from several applications may be simultaneously competing for resources. To address bandwidth contention, Kumar et. al [38] employed user space daemons running on application servers to predict anticipated traffic and assigning forwarding paths to applications using operator-configured policies. Fang et. al [286] proposed implementing host congestion controls to prevent excessive traffic influx into the network and multipath selection to achieve optimal network resource utilization. Jeyakumar et. al [290] viewed application bandwidth guarantees to be too stringent and proposed a weighted bandwidth sharing model among nested service endpoints allocating resources hierarchically at core fabric, rack, and individual machine level. The resulting operator defined per-application bandwidth sharing schemes are, however, highly dependent on the stability of application demands for long enough periods to optimize network traffic.

Efforts to relieve bandwidth contention from a topology perspective have seen the deployment of Clos networks gain momentum which counters link oversubscription by using large number of smaller switches, making failures much more localized and architecture more cost-effective [291]. Greenberg et. al [287] proposed VL2, a data center framework using 3-layer Clos topology with de-centralized load balancing to spread traffic across all available paths but instead of using per-application bandwidth allocation heavily relied only on TCP windowing to rate limit flows. Data center for the Facebook social networking website also reported using Clos topology to cope with

substantially high internal data center traffic [288]. Despite clustering per-application servers in proximity, the resulting Clos topology and cabling was considered to be incredibly complex. High-end network vendors propose similar solutions recommending unification of services to improve performance [292]. However, the application differentiation available at system and network level to assign machine limits and create end-to-end network topology per application does not explicitly consider user's application trends. Resource provisioning on a per-application basis, therefore, leads operators to pre-set network provisioning models dictating end-user experience regardless of real-time network conditions. A more user-centric approach where user requirements and activities are captured may present a resource abstraction model, which could offer service providers the ability to fine tune network resource share on the basis of user traffic classes in view of business and user requirements instead of isolated applications.

e) Application performance monitoring

Recent advances in virtualization and technologies have seen a range of application being hosted on multiple servers in cloud environments and private data centers. Monitoring and improving the performance of hosted applications requires the development of niche tools able to monitor the application traffic in virtual platforms and apply traffic management policies. SDN again due to decoupling of control logic from forwarding elements is seen as a key enabling technology in this domain. Liu G. and Wood T. [121] describe NetAlytics, a platform for large scale performance analysis which uses NFV technology to deploy software-based packet monitors in the network and an SDN management overlay to direct packets (flows) to these monitors. The system aims to diagnose application performance issues and the collected statistics also offer administrators an insight into application popularity. Maan et. al [122] developed a system for monitoring network flows at the edge, closer to the users in cloud based data centers. The work explores enabling flow monitoring in virtual switches in servers and proposes EMC2, a scalable network monitoring utility in cloud data centers to be used for performance evaluation of switch flow accounting methods. The evaluation recommends NetFlow [123], providing good network coverage with minimal use of computing resources to monitor application traffic in virtual environments and cloud based data centers. Hwang et. al [124] in addition to application monitoring, propose NetVM, providing customizable data plane processing services including firewalls, proxies and routers to be embedded with virtual servers. The authors highlight the benefits achieved in dynamically scaling, deploying and reprogramming of the embedded network applications using the SDN control plane.

f) Service improvement in heterogeneous network environments

Application delivery and service improvement to a significant extent also depends on the architecture and suitability of network elements in the data plane to efficiently implement customized traffic forwarding policies. The present and future trends in networking highlight the fact that heterogeneous networks ranging from wired, wireless, cellular, ad-hoc to vehicular environments and their inter-connection capability, together exponential growth in data usage [131] will play a crucial part in application delivery. SDN therefore, may offer operators the ability to integrate and share capacity on different shared physical media, a substantially challenging task with legacy networking infrastructure [132]. Applications and networks services can potentially use the SDN paradigm for routing and resource allocation in networks with heterogeneous characteristics such as different topology, physical medium and stability of connections. A few studies [55], [133] and [134] have, therefore, examined the scope of application delivery in different infrastructures including WiMAX, Wi-Fi access, etc. using SDN with satisfactory results. The OpenRoads [55] project for example, discusses seamless user service delivery between multiple wireless infrastructures. Other efforts carried out in [130], [133] and [134] offer enhanced application performance in wireless mesh environments using OpenFlow.

2.8.5 Limitations of current work

The majority of studies highlighted in the above discussion offer promising performance gains for individual applications utilizing a range of network management models ranging from a more 'application-aware' SDN paradigm to the use of novel SDN based monitoring techniques allowing performance measurement and QoS guarantees for certain services. The prevalent work in SDN based traffic optimization, therefore, focuses on improving the quality of individual applications and services such as video streaming or voice communications in several different network environments ranging from typical residential and enterprise networks to data centers. Other studies involving information-centric networking focus on bringing the data sources closer to the network edge, to again improve traffic conditions for the hosted application(s). Existing studies, however, do not specifically consider the impact that prioritising specific applications may have on other application traffic traversing the SDN fabric. Regardless of whether the network comprises of compatible or heterogeneous networking components, the end users in realistic environments may frequent a range of applications albeit in different proportions. SDN based traffic engineering schemes, therefore, need to consider the mix of user applications, which may result in several

workload profiles in the network, and the performance caveats the end users may experience as a consequence of individual service improvement.

This thesis seeks to highlight the effects isolated application performance models may have in SDN environments where users are frequenting a diverse range of applications. The presented research further aims to investigate methods for accurately capturing and incorporating user application trends in any subsequent SDN based traffic-engineering solution.

2.9 Conclusion

The present chapter considered the software defined networking technologies in detail. The northbound and southbound communication interfaces allow for several key protocols to be used in the SDN framework. Protocols such as OpenFlow on the southbound and RESTful API on the northbound controller interfaces, however, have seen significant adoption in both academic and industry research. In addition to communication protocols, recent years have also seen the development of several key controller platforms aimed at furthering the SDN paradigm and bringing substantial technical variety for researchers and operators to experiment and explore. Implementation of the SDN framework has seen production and test deployments in a range of avenues from data centers to residential premises. The SDN framework remains the subject of several research studies ranging from improving individual application and service performance to scalability studies finding an optimal solution to the controller placement problem in large networks. This thesis focuses on investigating the adverse impact that prioritising isolated application performance in SDN environments may have on users employing a mix of applications. The presented research further seeks to develop novel SDN traffic management solution, which accounts for user application trends in the network. The following section of the thesis (Part I) builds on this narrative and presents a feasibility study evaluating individual application usage ratios among residential users and also discusses the effects isolated application performance may have on the end users in an SDN framework. Furthermore, the section also discusses a profiling based traffic management scheme to be used in an SDN residential framework.

PART I – Residential Traffic Management

Chapter 3 Profiling User Application Trends

3.1 Introduction

Traffic classification and statistical trend analysis remain vital ingredients for designing effective traffic engineering and efficient resource management solution in computer networks. Previous studies highlighted several application classification techniques from packet and flow level network measurements and compared the accuracy evaluations of a number of approaches [161][163]. Application classification although, is only the first step in evaluating user network behaviour to create network management policies. Classified data flows are usually further subjected to QoS policies and the underlying network resources provisioned according to business requirements. However, as discussed previously in chapter 2, implementing QoS guarantees for individual application basis may not suit all the end users, especially those users frequenting a diverse range of applications. The present chapter details the utilization of profiling based traffic engineering as a substitute, employing actual network behaviour rather than individual services for implementing traffic management policies The derived profiling scheme offers operators a viable means of allocating network resources in view of actual user workload.

The remainder of this chapter is organized as follows. Section 3.2 compares typical QoS based traffic engineering model with a profiling based network management approach. Section 3.3 briefly highlights traffic classification challenges. Section 3.4 explores methods of characterizing user traffic behaviour by grouping user Internet activity attributes. Section 3.5 details the design methodology followed in the present chapter for extracting user traffic profiles. Section 3.6 discusses data collection methodology, inherent limitations and evaluates the resulting profiles. Section 3.7 further elaborates the proposed architecture and the potential application of utilizing the extracted user traffic profiles in software defined networks. Section 3.8 draws final conclusions.

3.2 QoS and Profiling based Traffic Engineering

Quality of service (QoS) aims at allocating priorities to different application flows to offer a certain level of network performance for the respective traffic. QoS policies may guarantee parameters such as data (bit) rate, delay, packet loss and jitter for individual services. In a typical SDN framework as depicted in Fig. 3.1, applications request connectivity between network

elements (NEs) through a centralized control plane and define individual QoS requirements per application. In view of limited network capacity, QoS policies implemented by the control plane for popular applications such as streaming, VoIP, interactive games, etc. ensure improved performance for the respective service. QoS schemes may rely on using legacy approaches such as Differentiated services (DiffServ) utilizing a prioritized model, marking packets according to the desired type of service (ToS). The centralized network controller or traffic management application, in response to these markings, can implement various queueing strategies in the data plane to offer isolated performance for the respective application traffic. Additionally, the SDN controller can also reserve resources such as the per-application routing paths and allocate bandwidth to reduce the effects of (any) network congestion on individual services. Application-awareness in SDN therefore, as highlighted earlier in chapter 2, allows the creation of forwarding policies offering performance for typical time-critical applications [58-61][167]. However, allowing one or more applications to control traffic forwarding by a forwarding construct that requires the use of new or existing resources may adversely affect other users who might be using an entirely different subset of applications. This would have a significant impact when, due to network congestion, applications such as VoIP or video conferencing would usually take priority over non time-sensitive services. For example, users frequenting applications such as web browsing and social networking may experience degraded performance during periods of peak traffic or perhaps due to prevalent constraints in networking resources as opposed to users watching live video streams due to network policy primitives favouring streaming applications.

Traffic profiling based policy implementation follows a relatively different network management approach. Meaningful statistical traffic patterns depicting user behaviour (profiles) can be extracted from classified traffic to be used in multiple areas, ranging from capacity planning, trend analysis to hardening network security [164][165]. User traffic profiles based on segregation of application usage data offer a detailed insight into traffic patterns and user behaviour and can be utilised for real-time workload characterisation and network management. However, integration of profiling controls in traditional fixed topology networks has remained substantially challenging. As discussed in [166], the sheer amount of network-wide flow data, summarised in network accounting schemes such as NetFlow or IPFIX records, remains largely unexplored for introducing user behaviour profiling based network intelligence and control. One of the primary reasons of lack of profiling based real-time service provisioning models is that due to change in traffic usage patterns, user traffic profiles may also change over time and the number of users in each derived profile is also subject to real-time variation. Consequently, traffic trend predictions based on lower layer network

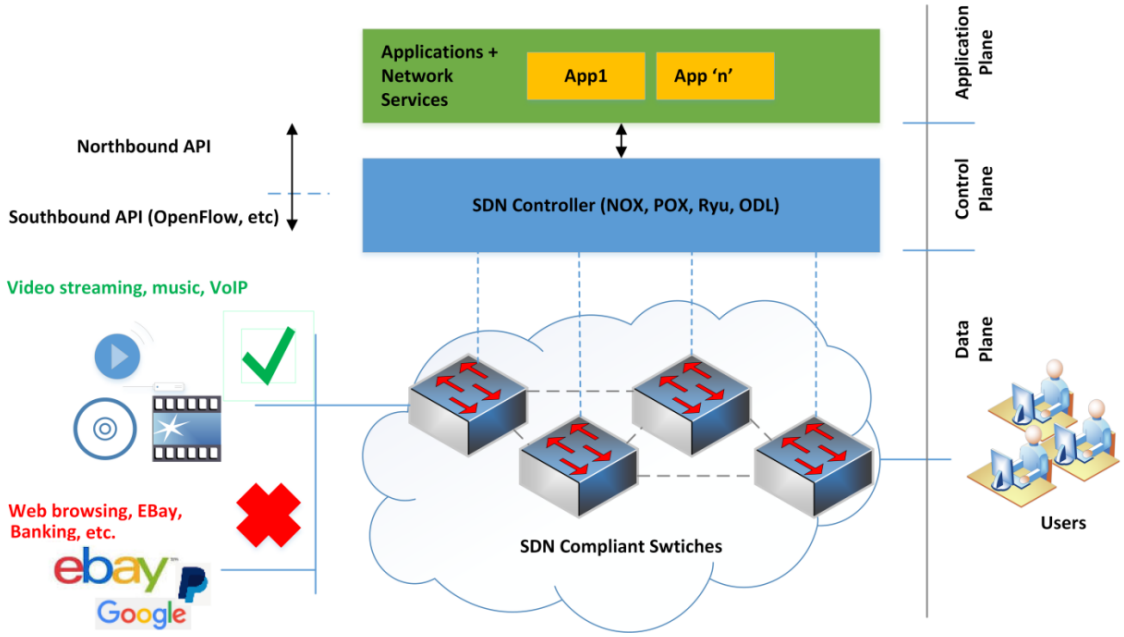


Figure 3.1. Individual application flows metering in SDN

parameters such as available bandwidth and packet loss statistics are usually considered enough for producing network control configurations in fixed hardware deployments that require repeated manual interventions for any policy update. Software defined networks (SDN) due to centralized control and real-time programmability may offer a greater potential to harness application level user traffic profiles for network control. Developing user traffic profiles based on actual network-wide user activity gives a thorough picture of application traffic trends and identifies resource heavy user classes. By calculating anticipated traffic based on user traffic profiles and the actual number of connected users per profile, an attempt can be made to allocate resources while accounting for a user-centric mix of applications in real-time in SDNs. A profiling based traffic engineering mechanism may provide operators the ability to allocate network resources based on real-time profile memberships and according to prevailing business requirements as opposed to individual application based QoS.

To this end, the present chapter evaluates the effectiveness of developing meaningful user traffic profiles from flow data collected from a residential hall for students comprising of 250 (single-tenant) studio flats over a thirty-day period between 01/11/2014 – 30-11/2014. Once the user traffic profiles are derived, the study further explores the potential advantage of integrating these user profiles in an SDN control framework to allow improved network management, accounting for a specific mix of applications.

3.3 Traffic classification challenges

User traffic classification methods have been extensively researched, with a common denominator being the fact that detecting individual application packets is not an easy task in both conventional and software defined networks. Port based application classification is prone to errors, as most Internet applications use dynamic ports, with some using tunnelling via HTTP/S and SRTP which makes classification virtually impossible. Standard QoS requirements embedded in packet headers are also often ignored [60]. Deep packet inspection (DPI) is useful, however, owing the computational cost associated with this technique, especially in real-time traffic identification, somewhat limits its wide adoption. Other methods for traffic classification include crowdsourcing based machine learning, application state analysis using DPI and DNS rendezvous classification [168]. Application traffic classification based on payload analysis or using other novel techniques is a research problem on its own and even crude classification can provide a great deal of insight even if based on port-based classifications from flow logs [166]. In order to satisfy the scalability issues, this chapter proposes a simple methodology of examining destination ports and IP addresses to identify application traffic from raw flow records. The presented work focuses on extracting meaningful user traffic profiles from readily available Netflow logs, ubiquitous in both legacy and SDN-based networking equipment and their viability in making potential traffic management decisions, specifically in the SDN. The approach integrates well with conventional and OpenFlow compliant hardware and software switches (e.g., Open vSwitch), which can collect/export NetFlow records for use in traffic analysis [123].

3.4 User traffic characterization

A number of features can characterize network traffic behaviour at varying levels of network hierarchy. For example, traffic characterization at the network prefix level considered in [166], presented a detailed overview of traffic characteristics at an ISP/backbone level using various features such as daily aggregate traffic, frequently used application ports and flow size distribution for traffic projection. Humberto et. al. in [169] characterized broadband user behaviour by analysing flow records and employed consumer behavioural modelling graphs (CBMG) to understand state transitions between application usage, while using k-means algorithm to classify residential and SOHO customers as per their usage trends. The present study intended to characterize traffic behaviour and associated flow statistics at user level by analysing user Internet activity or application usage. However, instead of focusing on destination port numbers and generic

characterization based on IANA allocated ports, real world applications and websites were grouped into specific tiers and user traffic behaviour was studied in relation to their corresponding usage of these grouped applications. After collecting the statistical data for these applications, users were also grouped into unique classes using machine learning techniques (clustering) based on similarity in application usage ratios. The concept of correlating variables by using clustering algorithms for pattern extraction is not new and has been previously used in numerous contexts. Heer and Chi in [170] used similar clustering for classifying web user traffic composition for three specific websites for capacity analysis. Yingqiu, Wei and Yunchun in [171] employed both supervised and un-supervised machine learning techniques on flow data to classify application level traffic and reported an accuracy of over 90% using k-means algorithm. However, these studies focused on application classification from flow records using clustering, while this study seeks to utilize the k-means algorithm for segregating users into classes based on their application trends. The next section examines the study design including categorization of network traffic and cluster analysis steps.

3.5 Profiling design

This study is based on the premise that per-user application level traffic and associated lower layer statistics can provide a thorough, discriminative measure of user activity. The defined user activity can, in turn, be used to implement user-centric traffic engineering solutions in SDNs, instead of formulating network policies around specific applications or lower layer network statistics. The profiling design therefore, seeks to satisfy the following objectives: (a) To discriminate among user activities, the application flows generated per user premises are collected and cluster analysed to derive user profiles for the observation period. (b) Depending on the diversity of user activities recorded in the resulting profiles, the study would aid in understanding the mix of user applications for subsequent utilization in designing profiling based traffic controls in SDN.

In order to determine short and medium variations of user activity in the present study, traffic from a residential student hall having 250 studio flats was collected over a 30 day period [01/11/2014 – 30/11/2014] and analysed to view the diversity in application usage captured in resulting user profiles. Each flat consisted of a single user, and the traffic collected per user premise presented an aggregation of multiple device activity (between 1-3 devices). The following sub-sections describe the design considerations and the k-means clustering algorithm used during the study.

3.5.1 Defining application tiers

The Office of National Statistics in the UK broadly grouped online user activities into eleven different categories ranging from sending and receiving emails to attending an online course [172]. A great degree of behavioural replication and similarity in traffic characteristics, however, usually exists among users' online activities and isolating each individual activity or application usage for user profiling would be counterintuitive. For example, online video streaming websites like YouTube and Netflix fall under the same umbrella of activity with rather similar traffic signature and can be tiered together under one category of user activity. Similarly Yahoo Mail, Gmail, Hotmail and traffic originating via POP3, SMTP protocols can be grouped as Email traffic without compromising the projection of actual activity. The motivation to use such a categorization technique is the fact that, besides reducing the computational cost of the clustering algorithm, the use of representative application tiers leads to fewer variables in corresponding feature vector for building meaningful traffic classes. For the purpose of this study, using typical internet usage applications/web visitations as presented in [52], user activity was broadly grouped in the following tiers: general web browsing (w), emailing (e), socializing (s), downloading (d), video streaming (v), gaming (g), communications (c) along with typical destination web sites and protocols, summarised in Table 3.1. On average, approximately forty popular applications or websites were included in the application groupings. Separate groups were created to account for any unknown traffic (t) originating outside the defined application tiers as well as network utilities (z) running in the background such as DNS.

3.5.2 Analysing user activity – feature vector design

Grouping applications into specific tiers, as per Table 3.1, results in defining a session of online activity per user by vector u_i [w_i, e_i, s_i, d_i, v_i, g_i, c_i, t_i, z_i]. Constituent application traffic parameters of vector u_i are unique website visits identified based on destination of user traffic, i.e. the destination IP address and protocol (with port number). The destination IP addresses of applications included in Table 3.1 were collected by running DNS queries on websites of interest repeatedly and in different time frames to accredit round-robin webserver load-balancing techniques employed by major websites which change destination IP addresses. These mappings were further cross referenced against mappings pre-configured in commercial network analysis tools like NetFlow Analyzer and [173] PRTG Network Monitor [174] for greater accuracy.

Table 3.1. Application Groups

Application Tier	Sample Popular Websites, Destination Port
Web browsing(w)	General browsing using http(s) except below categories
Emailing(e)	Gmail, Ymail, AOL, Outlook.com, SMTP, POP3, IMAP
Socializing (s)	Facebook, Twitter, Blogger, WordPress, Tumblr, LinkedIn
Downloading(d)	BitTorrent, VUZE, uTorrent, FTP, SmartFTP, FileZilla, CoreFTP
Video Streaming(v)	YouTube, Netflix, Lovefilm, Megavideo, Metacafe, DailyMotion
Games (g)	n4g, uk-ign, freelotto, 8-ball pool, Warcraft, Team Fortress
Communication (c)	Skype, Net2Phone, MSN Messenger, Yahoo Messenger, GTalk
Unknown Traffic (t)	Unaccounted TCP and UDP traffic
Network utility (z)	DNS queries, Multicast traffic

3.5.3 K-means clustering algorithm

The primary aim of using clustering in the present study was to derive a meaningful set of user traffic profiles by partitioning users into different groups based on their application usage, which would give a complete overview of all user activities across the entire subscriber base. This required designing a computationally efficient clustering technique. As discussed earlier in section 3.2.3, k-means is a prominent clustering algorithm previously used in similar network related studies. The profiling methodology in the present chapter therefore, primarily used k-means clustering algorithm which aims at minimizing a given number of vectors by choosing k random vectors as initial cluster centers and assigning each vector to a cluster as determined by a distance metric comparison with the cluster center (a squared error function) given in Eq. (3.1). Cluster centers are then recomputed as the average (or mean) of the cluster members. This iteration continues repeatedly, ending either when the clusters converge or a pre-defined number of iterations have passed [175]. Compared to other methods such as hierarchical clustering, k-means works well with a large number of variables and produces tighter clusters.

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} ||x_i^j - c_j||^2 \quad (3.1)$$

In the above equation, $||x_i^j - c_j||^2$ is distance between individual values in a given vector and the cluster center c_j, n equals the size of the sample space (number of users) and k is the chosen value for number of unique clusters (centroids). Hence, using k-means, n entities can be partitioned into k groups. Choosing a value of k is of significant importance as it directly influences the number of resulting groups i.e. derived user traffic profiles in the present case. As evident from Eq. 3.1, the closer the value of k (number of centroids) to the number of users *n*, the greater will be the resemblance between adjacent user traffic profiles rendering them meaningless, whereas a smaller

value would reduce the internal cohesion among members of a profile and over-generalize the uniqueness of users. This particular aspect will be discussed later in detail in section 3.6.2 while examining results.

3.6 Evaluation

3.6.1 Data collection

The study used flow records collected from a residential hall for students comprising of 250 studio flats. Each of the flats had an independent user CPE (router) connected via LAN to central switches and Netflow logs were collected at the building default gateway (router) for all outbound traffic originating from each customer router. Each studio flat comprised a minimum of one and a maximum three user devices. For the purpose of user traffic profiling, the study primarily concentrated on outbound user generated flows as these give an accurate representation of user actions, however, total traffic transferred for both inbound and outbound traffic was still collected to further examine the traffic distribution per user profile. NetFlow logs were concatenated every 24 hours over 30 days and parsed [Appendix – 1.1], to calculate the application traffic composition vector per user as depicted in Table. 3.2 (truncated due to space). Network traffic for a user u_1 on a specific day [30/11/2014] can therefore, be represented by vector as given in Eq. 3.2. Each entity in Eq. 3.2 represents the percentage of flows generated by the user u_1 towards each of the application tiers given in Table 3.1, for the given day.

$$u_1\,[30/11/2014] = [83\ 0.5\ 1.7\ 1.8\ 2\ 0.1\ 0.7\ 9.9\ 0.1] \qquad (3.2)$$

To account for limitations of the previously discussed technique for mapping IP addresses to website domains, individual user traffic vectors were excluded from subsequent profiling where these mappings were unsuccessful in identifying greater than 10% user traffic (ti > 10%). As a whole this did not significantly reduce the sample space (number of users for effective traffic profiling). The percentage of users that were excluded due to unaccounted application level traffic was always

Table 3.2. Traffic Composition Vectors [30/11/2014]

$u_i = [w_i, e_i, s_i, d_i, v_i, g_i, c_i, t_i, z_i]$											
i	**User router IP**	**Flows**	**w %**	**e %**	**s %**	**d %**	**v %**	**g %**	**c %**	**t %**	**z %**
1	10.0.1.22	115	83	0.5	1.7	1.8	2	0.1	0.7	9.9	0.1
.	…	…	…	…	…	…	…	…	…	….	….

considerably less than a maximum observed value of 12% over any consecutive 24 hours during the 30-day data collection time span.

3.6.2 Clustering users

A total of 7594 unique user traffic distribution vectors for the user were examined comprising approximately 50.3 million flows. Once flow records were concatenated for each day k-means clustering algorithm was implemented on resulting vectors (Table 3.2) using R script [176][Appendix – 2.1]. Since user traffic profiling was based on application usage, the assigned source IP addresses of user CPE (routers) and numeric value of total flows were scalar entities for this analysis and ignored from a clustering perspective. In addition, since general network service traffic (z_i) such as DNS queries are not a user-triggered application but a functional one and technically generated by other application traffic, it was also excluded while clustering users and later separately calculated as a percentage of total network flows generated per profile.

As previously mentioned, the primary aim of the clustering algorithm was to identify a smaller number of anticipated usage patterns (defining for user traffic profiles) that can cover the complete subscriber base. The profiles had to be meaningful enough to reflect user activities without compromising on the mutual exclusivity of the profiles. Therefore, using values of k starting from k=2, the size of the clusters and number of users per cluster was analysed as given in Table 3.3. Choosing a lower value k resulted in a substantial membership size per profile but the ratio of application traffic distribution per profile showed a great deal of over fitting of users in resulting profiles to give a useful perspective. With higher values of k >4, profiles were too refined with the majority of users only falling in particular profiles, rendering the number of users and traffic distribution among other groups negligibly small. For example, k=6, resulted in six unique profiles

Table 3.3. Clusters vs Membership Size

Number of clusters *k*	Cluster Membership Size
2	6866, 728
3	6089, 1018, 487
4	5913, 1143, 283, 255
5	3949, 2837, 781, 17, 10
6	4280, 2198, 726, 350, 26, 14
7	3915, 2473, 793, 373, 17, 14, 9

with significant number of users in four profiles (4280, 2198, 726 and 350). However, in the remaining two profiles total number of users (26 and 14) accounted for less than 0.01% of total members. The corresponding application traffic distribution ratios for these two profiles were also found to be insignificant to be considered meaningful at this stage. The same trend continued up to the tested k=7. As a result, for the time period under consideration and the combined traffic flows captured per user premises, k=4 was considered to give a balance between these two extremes catering for both heavy membership profiles as well as lower ones without compromising too much on mutual exclusivity between profiles. The resulting profiles not only segregated the users into different profiles based on the variation in their respective application usage but also had considerable mermbership size. For k=4, the user traffic profiles are further analysed in the following subsection.

3.6.3 Results

The resulting traffic profiles (k=4), are given in Fig. 3.2, detailing application traffic distribution among user traffic profiles, reflecting the different classes of users present in the network. Users falling in profile 1 concentrated on web browsing with minimal usage of other applications. Profile 2 represented lower web browsing (only 7.09%) with slightly more usage of emails and socializing than profile 1 but downloading from torrents and file sharing via FTP stands out from other attributes and forms major bulk of these users (45.7%). User profile 3 also included web browsing (50.07%), but the distribution of other activities such as emails, downloads, streaming and games is slightly higher than the one in profile 1. The users falling in this profile were using a somewhat greater amount of all the applications compared to other profiles. Finally, user profile 4 clustered users for which communication applications form a large portion of their traffic (56.07%), with corresponding DNS connections also significantly higher than rest of the profiles. Network traffic statistics detailing data transfer, number of flows and size of clusters per user traffic profile are presented in Table 3.4. The number of connected users per profile remained relatively static over the 30 day evaluation as depicted in Fig. 3.3 (a) with profile 1 accounting for the highest number of users per 24 hour time period whereas the lowest number of users relates to profile 4. The total traffic volume, the sum of incoming and outgoing bytes per day for each of the traffic profiles is given in Fig. 3.3 (b). Profile 1 had the highest amount of data transfer both for the incoming as well as outgoing traffic. This was followed by profile 3 and profile 2. The lowest amount of traffic generated was in profile 4 comprising users who were mainly using communication related applications such as real-time messaging and communication. The cluster size varied considerably

between profiles with the bulk of users falling in profile 1 (5913), followed by profile 3 (1143) while profile 2 (283) and profile 4 (255) accounted for the smallest number of users.

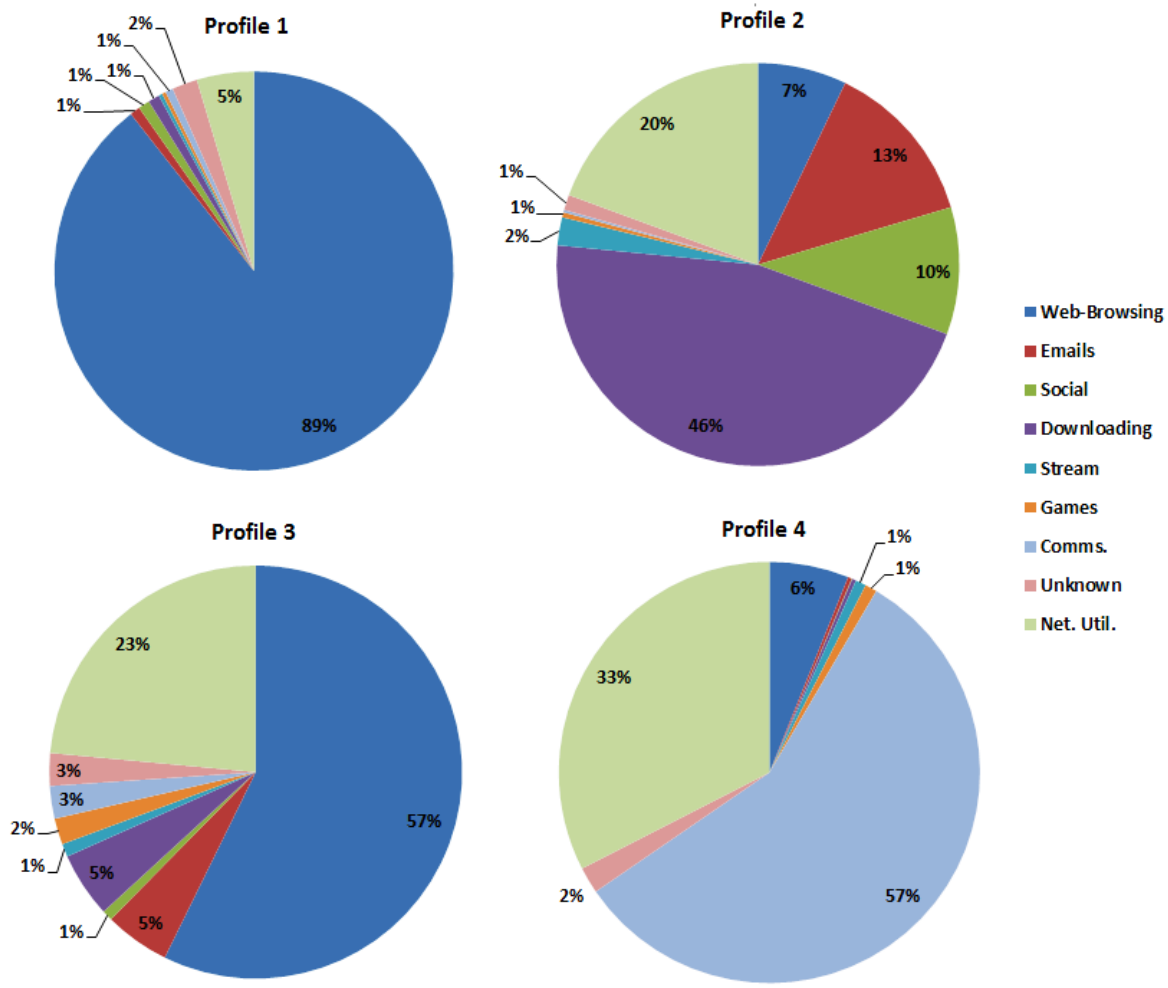


Figure 3.2. User Traffic Profiles

Table 3.4. Traffic Statistics per Profile

Stats.	Profile 1	Profile 2	Profile 3	Profile 4
Avg. outgoing bytes per day (GB)	17.40	1.61	2.87	0.19
Avg. incoming bytes per day (GB)	292.02	10.18	47.40	1.27
Avg. total traffic per day (GB)	309.42	11.79	50.26	1.46
Total traffic per month (GB)	9282.99	354.42	1508.48	22.84
Total traffic per day per user	1.57	1.31	1.32	0.09
Avg. users per day	197	9	38	8
Avg. % flows per day	57.74%	30.43%	11.80%	0.014%
Cluster size	5913	283	1143	255

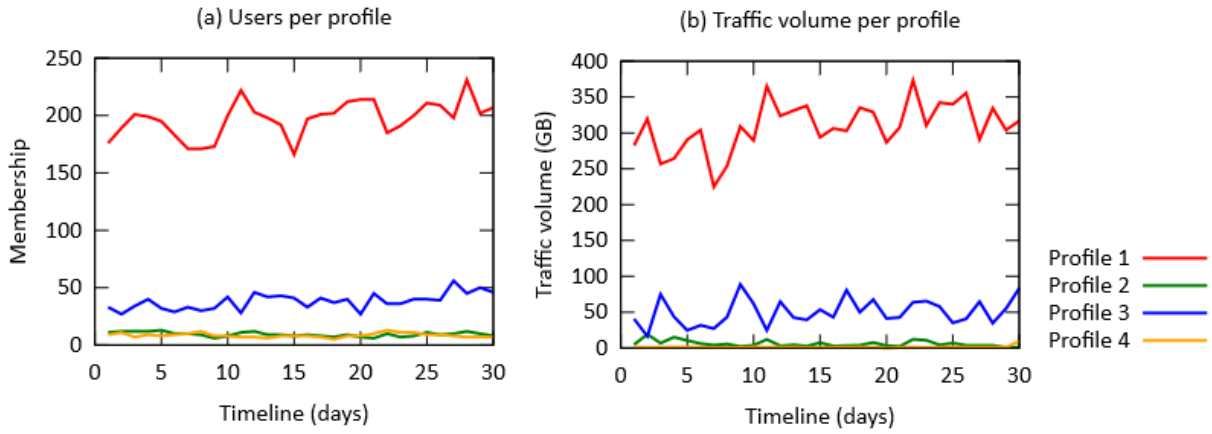


Figure 3.3. (a) Aggregate traffic distribution per profile and (b) Users per traffic profile (30 days)

3.7 Applicability in software defined networking

From the user traffic profiling analysis, a significant degree of variation can, therefore, be observed among users' activities. While the majority of users fall within one user traffic profile (i.e., profile 1), there were however, a significant portion of subscribers who differed from the mainstream in terms of their application usage ratios, and the amount of data transferred. Implementing isolated application performance controls on users with such varying application trends depicted in the extracted traffic profiles may definitely result in adverse performance for some traffic classes. For example, improving performance of communication related applications such as Skype in an SDN based environment by creating favourable flow forwarding constructs may be of benefit to users in profile 4. During periods of high traffic which may lead to temporal congestion due to constrained capacity, profile 4 users may continue to experience reasonable performance due to VoIP QoS guarantees. However, other users in profile 1 and profile 3 who are mainly engaged in web browsing activities may experience poor performance. Profiling user traffic therefore gives network operators additional insight into user activities and resource utilization to design and implement necessary network policies.

Extending the above rationale to the context of software defined networks, there is a potential to employ user traffic profiles for effective traffic management. A diagram illustrating the incorporation of profiling based controls in the SDN is presented in Fig. 3.4. The framework comprises of a traffic profiling mechanism and a traffic manager. The traffic profiling framework may collect flow measurements from the data plane, which are pre-processed and subjected to cluster analysis to extract user traffic profiles. Utilizing the profile statistics as depicted earlier in Table 3.4, the traffic manager gains a predictive view of traffic by monitoring number of connected

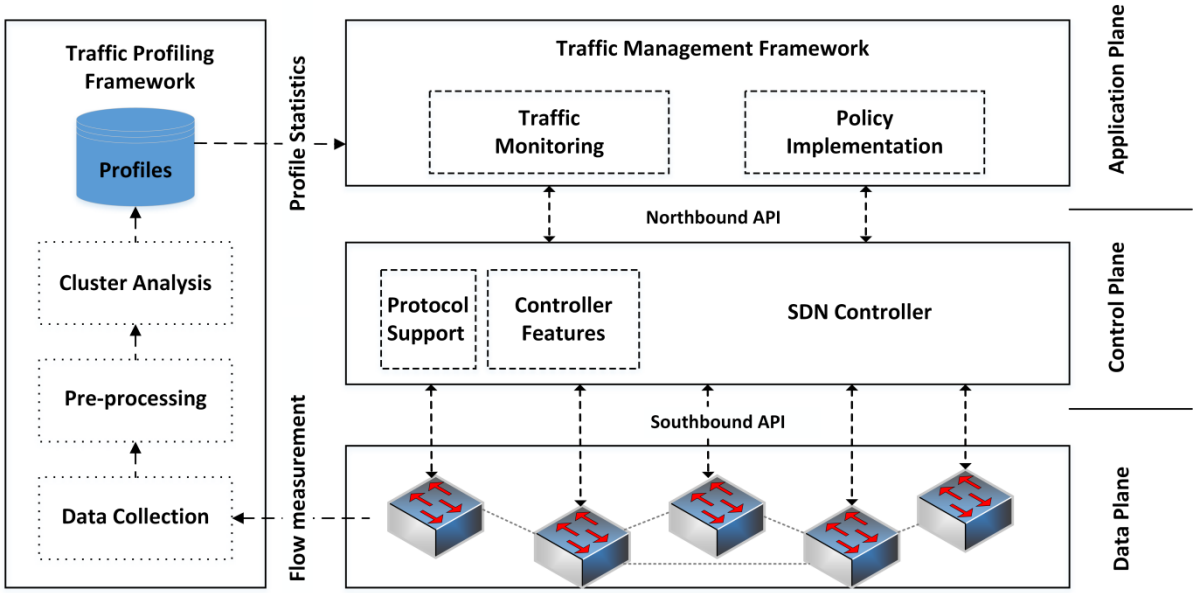


Figure 3.4. Incorporating User Profiling Controls in SDN Framework

users of each profile in real-time. The traffic profiles and incorporated statistics, can thereafter be used for implementing profiling based traffic engineering such as the rate limiting of traffic flows per user profile via flow tables in individual network elements, which are readily modifiable by the controller using a southbound API such as the OpenFlow protocol.

Traffic could also be effectively load-balanced by the controller so that resource intensive traffic profiles are off-loaded to high speed layer 1 links (e.g., optical cables) while others may be redirected to or continue using relatively slower links as applicable based on the network topology. Commercially, SDN controllers have already been developed to offload network traffic from specific applications generating big data sets to optical networks in cloud data center environments for improved efficiency [177]. User traffic profiling, however, employs actual user activities and changing traffic conditions to balance network resources rather than rely on specific applications or other L2/L3 criteria such as Differentiated Services Code Point (DSCP) for traffic management. An operator using the SDN controller(s) may define policy control based on user profiles and underlying network conditions to fully exploit real-time configuration capability of the data forwarding plane by defining action sets, modifying flow entries and selecting outgoing ports/links in NEs based on an accurate estimation and distribution of user traffic to balance or optimize certain user classes.

Additionally, from a network monitoring perspective, once user traffic profiles have been derived, the number of users and their respective data transfer trends, as depicted in Fig. 3.3 (a) and 3.3 (b), reduce the need and frequency of profile re-computations, leading to only incremental adjustments over time. For example, user traffic profiles may be computed in the offline mode once every month, in a round-robin fashion, to avoid temporary overload while the total number of users and their traffic volume (total data transfer) are monitored in real-time every 24 hours to check if these conform to the expected values and match the profiles. If anomalies are observed (such as a significant number of users falling out of trend with respect to total data transferred), the profiles and relevant policies may be updated or re-evaluated.

3.8 Conclusion

This chapter proposed a method to derive user traffic profiles by extracting aggregate application level data per user premises from NetFlow records and then clustering users together based on their respective application usage trends. The resulting traffic profiles showed a considerable degree of variation in user Internet activities and associated attributes such as average number of flows, average data transferred and the distribution of users per profile. While prior studies have offered isolated application level traffic engineering in SDNs, such methods may result in inferior performance for a subset of users who combine a different range of applications or even those using same applications with divergent usage ratios as evident from the derived profiles. Integrating such user traffic profiles for traffic optimization is challenging in conventional fixed topology networks due to ever-changing user activities and the manual interventions required in updating policies. Software defined networks, however, through a centralized control framework make real-time programmability of network elements much easier. The present chapter therefore, proposed implementing flow metering and rate limiting based on user traffic profiles instead of applications and also re-routing resource intensive traffic profiles over alternate links as applicable depending on actual network topology. This would provide a much more comprehensive traffic optimization solution in SDNs while accounting for a user-centric mix of applications.

Furthermore, the preliminary profiling investigation carried out in this chapter used aggregate traffic from each of the residential housings comprising of multiple users /devices. The following chapter explores profile extraction for each user device independently per customer premises, employed in the present study. Profile derivation in multi-device user environments (such as

residential networks) provides further insight into user behaviour for designing and deploying subsequent user-centric SDN based solutions in residential networking.

Chapter 4 Evaluating User Traffic Profile Stability

4.1 Introduction

User traffic characterization is of fundamental importance in modern networking environments for understanding user behaviour that assists administrators and service providers in traffic optimization, capacity planning, and improving security. Analysing network workload usually requires collecting statistics around multiple traffic features, ranging from total traffic volume, number and duration of user connections to application usage per consumer and provides network managers the ability to anticipate both business and technological updates [169][178-183]. Proliferation of high speed residential broadband access over recent years, coupled with the growing number of devices per household have compelled providers to seek ways of modelling and understanding user behaviour for improved service differentiation and context based charging [179][180]. As examined earlier in chapter 3, the segregation of users into traffic classes or profiles as per their application usage simplifies the understanding and visualizing of user behaviour in the context of network policy management. User traffic profiling in current residential and enterprise networks, however, is no longer limited to a single device but multiple devices. Effective network management particularly in modern networks, for example, residential premises where customers usually have more than one device sharing a common internet connection, requires an understanding of traffic patterns at the local level, inside the network as much as externally [179][182]. Investigating and evaluating the frequency of profile transitions among multiple devices per individual residential premises may give additional insight into user behaviour for subsequent utilization in a residential SDN traffic management solution. This chapter, therefore, extends the profiling methodology examined earlier to multiple users (devices) in each residential premises, considered in chapter 3. Furthermore, three different clustering algorithms, the k-means, hierarchical agglomerative technique and density-based spatial clustering (DBSCAN) are compared to explore the resulting profiles and evaluate the technique which provides more meaningful results. The derived profiles are benchmarked for stability and inter-profile transitions per user device also studied, to ascertain the frequency of user behaviour changes with respect to each device.

The profiling methodology follows (a) grouping popular internet applications into distinct categories and classifying traffic using destination web server IP addresses and port numbers, (b) developing device traffic profiles based on application usage trends using unsupervised cluster analysis and (c)

evaluating the probability of inter-profile changes among devices per premises to establish transition trends and re-profiling frequency. Finally, the derived profile baselines are further analysed for possible use in an SDN traffic monitoring and management solution targeting residential networks.

The rest of this chapter is organized as follows. Section 4.2 highlights user behaviour characterization in multi-device environments. Section 4.3 presents the technique used for data collection of each user device from the respective residential CPE (routers), and feature based clustering techniques. Section 4.4 evaluates the resulting traffic profiles and investigates profile stability over the duration of the study as well as an analysis of inter-profile correlations. Section 4.5 discusses the incorporation of extracted profiles in residential SDN environments. Final conclusions are drawn in section 4.6.

4.2 Multi-device user environments

The proliferation of high-speed residential broadband and increase in the number of devices per household has highlighted the need to understand device traffic from inside the network for effective network management and improved security. The predominant method of characterising user behaviour in both enterprise and residential networks has been to cluster users based on peculiarities in traffic features, using flow and packet based measurements or report these as standalone attributes for monitoring overall network traffic as highlighted in [179], [181], [169] and [182]. Xu. et. al [179], used IANA assignment of port numbers as the primary feature for clustering device traffic inside user residences and identifying internet malware. To understand variations in application usage among residential and SOHO broadband consumers, Humberto et. al [169] employed k-means clustering and state transition graphs to depict the relationship between users' Internet activities. Similarly, Jinbang et. al [182] studied user traffic profiling in modern enterprise networks to understand the contrast between external and internal activities being carried out in the network. From an external, service provider perspective, Jiang et. al [181] used k-means clustering and aggregate consumer traffic flow to profile users on a number of traffic features including application usage as well as flow-level parameters.

Profiling individual user devices in modern residential premises having multiple devices, as illustrated in Fig. 4.1, presents an interesting avenue for understanding the temporal nature of user

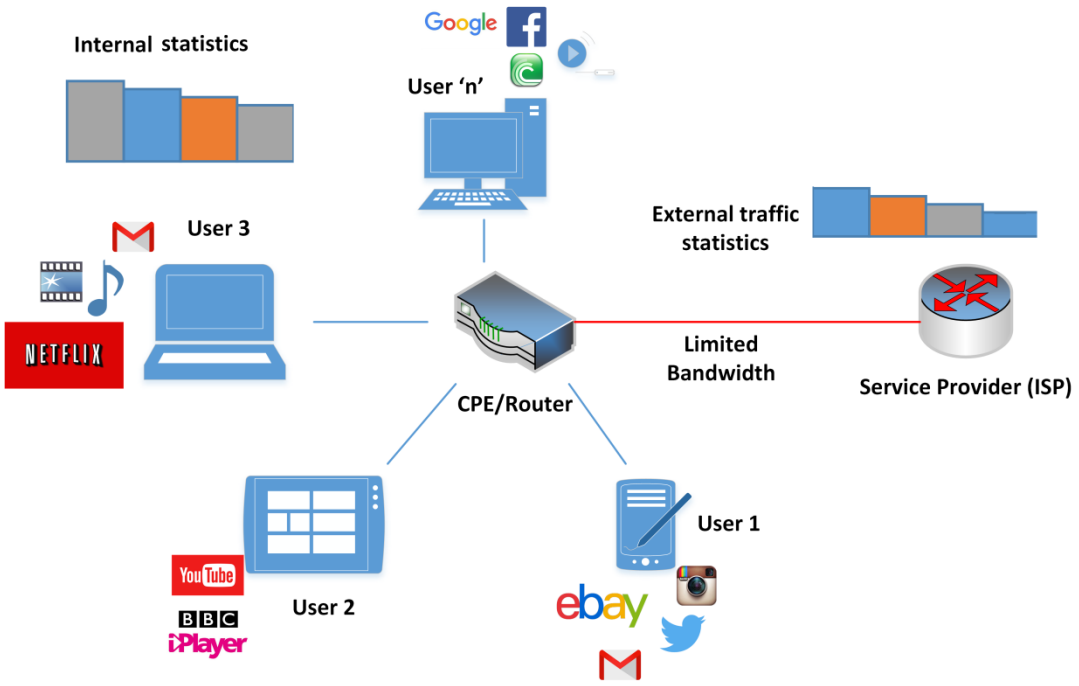


Figure 4.1. A typical multi-device user network (residential)

activity per device. The profiling of application trends inside such multi-device environments aids in determining whether the derived traffic classes lend considerable consistency over time to serve as an effective tool for network monitoring and management. In residential SDN based traffic engineering, for example, the enhanced trend visualization and application usage offered by traffic profiles could aid in the creation of per profile dynamic resource allocation policies, according to the requirements of the residential subscribers or externally by the service provider.

The primary necessity in user traffic profiling, however, remains, the need to classify application traffic. As highlighted in chapter 3, novel methods such as machine learning classification algorithms or deep packet inspection techniques either involve substantial processing overhead or highly sanitized and pre-processed records for getting meaningful results as detailed in [183-186]. Service providers and network administrators have an imminent need for extrapolating subscriber application usage and rely on commodity tools like NetFlow Analyser [173] and PRTG Network Monitor [174] which partially circumvent the traffic identification problem by including pre-defined customisable webserver IP addresses of frequently used applications and websites, matching these to user requests for accounting. This scheme may seem limited but with careful planning and continuous updating can be effectively used to report top applications and website visitations. The present chapter, therefore, continued to utilize the IP address and port mapping method previously employed from chapter 3 for identifying user application traffic. The next section discusses the

methodology employed for data collection as well as the different clustering techniques used for user traffic profiling.

4.3 Profiling implementation

The present study, building on the preliminary investigation carried out in chapter 3 aimed at profiling user devices in each residential premises based on the respective devices' application trends. The frequency of change in user activity was further assessed by observing profile transitions per user-device to evaluate if derived profiles granted significant stability over time to serve as benchmarks for formulating network management policies. The following subsections detail the updates to application groupings and the monitoring setup employed for per device profile derivation and describe the clustering algorithms used.

4.3.1 Application categorization

User traffic was classified by matching user requests (NetFlow records) against destination IP addresses and ports used by popular internet applications as mentioned earlier. These were further cross-referenced against commercial tools such as NetFlow Analyser [173] and PRTG Network Monitor [174] for greater accuracy [Appendix – 1.1]. To account for replication in nature of user activities, applications were once again grouped into distinct categories as depicted in Table 4.1. Given the replication of traffic footprint between social tier and the web browsing tier observed during the profiling analysis in chapter 3, the social tier was merged with browsing to concise the application groupings and the resulting profiles. A unique website visitation or application usage on user device could, therefore, be defined by the updated vector u_{ij} given in Eq. 4.1.

$$u_{ij} = [w_{ij}, e_{ij}, d_{ij}, v_{ij}, g_{ij}, c_{ij}, t_{ij}, z_{ij}] \quad (4.1)$$

In equation 4.1 above, *i* and *j* are unique per user premises and user device respectively and remaining entities represent the application usage percentage in accordance with the updated application group given in Table 4.1.

4.3.2 Monitoring setup

The study used NetFlow records exported from the default gateway of a residential student complex housing 250 user premises (studio flats) over a span of four weeks from 01/02/2015 to

28/02/2015. Each flat comprised a single user, having their CPEs such as home routers for connecting multiple devices to the Internet. Each user had between one and three devices and all user (premises) routers connected to the dedicated ports on two distribution switches, responsible for forwarding and receiving traffic from the default gateway as shown in Fig 4.2. The SNMP instances running on the distribution switches were used to report the IP address of each user device connected to each customer router (mapped to the respective distribution switch port), to account per device traffic flows.

4.3.3 Data Collection and Pre-processing

NetFlow records collected by the central collector were concatenated and customised every 24 hours to build flow records incorporating traffic statistics. The resulting logs were processed to quantize user device activity (flows) as a percentage of application usage in accordance with Table 4.1. Afterwards, SNMP monitoring information from access switches was used to associate the individual devices to user premises. Table 4.2 depicts a snapshot of the traffic

Table 4.1. Updated Application Groups

Application Tier	Sample Popular Websites, Destination Port
Web browsing(w)	Web browsing: http(s) except below groups
Emailing(e)	Gmail, Ymail, AOL, Outlook.com, SMTP, POP3, IMAP
Downloading(d)	BitTorrent, VUZE, uTorrent, FTP, SmartFTP, FileZilla, CoreFTP
Video Streaming(v)	YouTube, Netflix, Lovefilm, Megavideo, Metacafe, DailyMotion
Games (g)	n4g, uk-ign, freelotto, 8-ball pool, Warcraft, Team Fortress
Communication (c)	Skype, Net2Phone, MSN Messenger, Yahoo Messenger, GTalk
Unknown Traffic (t)	Unaccounted TCP and UDP traffic
Network utility (z)	DNS queries, Multicast traffic

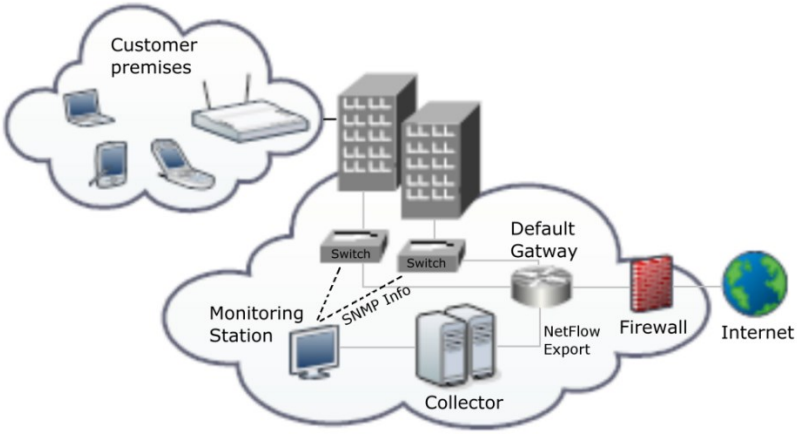


Figure 4.2. Network monitoring setup

composition matrix for a single day. Network activity for a user device $u_{1,1}$ on a specific 24hour interval, e.g. [01/02/2015], could therefore be represented by the application distribution vector given in Eq. 4.2. In Eq. 4.2 each quantity represents the percentage of flows generated by the user's device towards the application tiers given in Table 4.1.

$$u_{1,1}\,[01/02/2015] = [76\ 0.2\ 1.1\ 1.4\ 7\ 0.3\ 1.8\ 12.2] \tag{4.2}$$

Once application distribution vectors per user device were collected, traffic profiling was done using both agglomerative hierarchical clustering as well as Hartigan and Wong implementation of k-means [189] and DBSCAN [209], using R [176] [Appendix - 2.1, 2.2, 2.3]. To gain a better overall understanding of the different users, unidentified traffic (z) was not excluded during cluster analysis (as done previously in chapter 3), but included as a feature during clustering. The resulting traffic profiles and associated analysis is detailed in the following section.

4.3.4 Traffic profiling

The objective of this profiling study is to seggregate user devices from the user premises into unique profiles. Furthermore, the profiling scheme has to extract profile clusters, ideally eliminating or minimizing outlier groups to a minimum. Eliminiation of outliers would contribute to having a reasonable membership size (e.g., 10-20 members) for even a minimal activity profile. The extracted device profiles may then be accordingly used to define user-centric network management primitives in a residential SDN framework.

To achieve the above objectives in terms of profile extraction, three prominent un-supervised clustering techniques were employed: hierarchical agglomerative clustering [187], k-means [175], and density-based spatial clustering of applications with noise (DBSCAN) [209]. Hierarchical clustering puts each observation in its own cluster and then calculates the distances between all

Table 4.2. Traffic Composition Statistics [01/02/2015]

User and Device ID			**Flows**	**Application Usage** $u_{ij} = [w_{ij}, e_{ij}, d_{ij}, v_{ij}, g_{ij}, c_{ij}, t_{ij}, z_{ij}]$								**Flow Duration**		**Data Volume**	
Us	**Devi**	**SrcIP**	**Flo**	**w**	**e**	**d**	**v**	**g**	**c**	**t**	**z%**	**Tx**	**Rx**	**Tx**	**Rx (B)**
1	1	10.0.1.	115	76	0.	1.	1.	7	0.	1.	12.	4.74	2.12	388	98756
1	2	10.0.2.	85	24	2	1	9	0.	3	2.	32.	2.79	1.79	856	55587
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…

observations, pairing the closest two in a recurring fashion. The linkage function between the (pair-wise) sets of observations may use the maxmimum distance (or complete linkage) or the more advanced Ward's method, which uses the decrease in variance for the respective clusters being merged. K-means on the other hand, as mentioned earlier minimizes a given number of vectors by choosing *k* random vectors as initial cluster centers and assigning each vector to a cluster as determined by distance metric (Euclidean) comparison with the cluster center (a squared error function) as given in Eq. 3.1, earlier in chapter 3. Cluster centers are then recomputed as the average of the cluster members and the iteration continues repeatedly, ending either when the clusters converge or after performing a specified number of iterations [175]. In Eq. 3.1, with respect to multi-device user environments, c_j continues represents the cluster center, *n* the size of the sample space and *k* the chosen value for number of unique clusters (centroids). Hence, using k-means, *n* entities, translating for user devices in the present case, can be partitioned into *k* groups or profiles. The value of *k* is of significant importance as it directly influences the number of traffic profiles and affects over-fitting of users into profiles. Rather than relying exclusively on manual examination of trends in each cluster, as used earlier, the optimal value of *k* was calculated using the automated Everitt and Hothorn technique [188], in tandem with manual examination of derived profiles. The technique aims at finding the curve in cluster convergence with respect to increasing *k*, with only minor variation beyond a certain level i.e the knee of the plot suggesting a suitable value for cluster numbers.

In addition to k-means and hierarchical cluster analysis, the DBSCAN algorithm is among the common techniques used in unsupervised cluster analysis. Given a set of data points in space, the algorithm groups points that are closer together (having many neighbours). Data points falling in low-density regions with minimum nearby neighbours are classified as outliers. As with all data mining techniques, DBSCAN also requires prior parameter estimation for successful clustering. However, unlike k-means, DBSCAN does not require an identification of the number of clusters in the data a priori. The algorithm requires two parameters: *ε*, the size of the epsilon neighbourhood, and *minPts*, the number of minimum data points that are required to define a dense region. DBSCAN starts by selecting an arbitrary data point not visited before and computes its ε-neighbourhood leading to the start of a cluster if the value conforms to the minPts defined by the user. If the data point is found to be dense enough (according to *ε* and *minPts*), data points within ε-neighbourhood also form a part of this cluster. The process continues until all the density-connected points are found resulting in a complete cluster. If, however, the value of data points within ε is below minPts, the selected data point is labelled as noise, which may or may not be

made a part of a cluster in subsequent iterations. The process continues with the selection of a new un-visited data point. With regards to parameter estimation, the value of ε may be computed using a k-distance graph (k-NN plot), where the curve in the graph points to an appropriate value of ε [266]. A very small value may result in a great deal of noise points and unclustered data, while a large value may result in majority of data points being under the same cluster. The minPts parameter may be computed according to $minPts \geqslant D + 1$, where D is the dimension of the data points to be clustered. Again, a minimum value for *minPts* such as 1 would result in each data point forming a cluster, while a very large value may result in the merging of otherwise independent clusters. Parameter estimation and resulting clusters, translating in user traffic profiles in the present case for the respective clustering algorithms will, therefore, be considered in detail to derive meaningful user profiles during evaluation in section 4.4.

4.4 Evaluation

4.4.1 Cluster Analysis

A total of 10095 unique traffic distribution vectors for user devices were examined comprising approximately 178.21 million flows. The resulting vectors were subjected to hierarchical and k-means clustering and cluster memberships were evaluated for cluster sizes ranging between 2 to 10 as depicted in Table 4.3. Using the default maximum distance linkage (or complete) method in hierarchical clustering, profile membership numbers resulted in minimal number of observations in some clusters. The more advanced Ward's method and k-means, however, resulted in much more significant membership numbers across all the derived clusters. The next step was finding the optimal number of clusters (translating for traffic profiles) that would appropriately reflect user activities. Clusters derived using k-means were examined starting from k=2, using Everitt and Hothorn technique given in [188]. This technique aims to find the curve in plot of 'within groups sum of squares distance' per observation in each cluster against k for suggesting an appropriate number of profiles that fit the input data. The corresponding plot for the present data is given in Fig. 4.3 where a significant drop can be seen up to a cluster size k=6, with minimal variations up to k=15, which indicates an optimal value of 6 profiles. Application distribution ratios for profiles derived using both hierarchical clustering (Ward's method) and k-means were afterwards, compared to ascertain which set presented meaningful results. While profile membership numbers per cluster using either method were quite similar, profiles derived using k-means gave a much clearer segregation of user activities. For example, for six profiles, hierarchical clustering resulted in three

Table 4.3. Profile Membership Distribution per Cluster (hclust and k-means)

# Clusters	Hierarchical Clustering (method= max)	Hierarchical Clustering (method=ward)	k-means
2	10094, 1	6316, 3779	8236, 1859
3	10002, 92, 1	6316, 2365, 1414	6172, 2576, 1347
4	9742, 260, 92, 1	6316, 2365, 1216 , 198	5013, 2642, 1272, 1168
5	9742, 255, 92, 5, 1	3904, 2365, 2412, 1216 , 198	6339, 2473, 970, 228, 85
6	8815, 927, 255, 92, 5, 1	3904, 2412, 2365, 687, 529, 198	5013, 2644, 1249, 880, 224, 85
7	7868, 947, 920, 255, 92, 5, 1	3904, 2412, 1253, 1112, 687, 529, 198	3965, 2660, 1538, 828, 224, 795, 85
8	7868, 947, 920, 255, 90, 7, 5, 1	3904, 2412, 1253, 1022, 687, 529, 198, 90	3736, 2607, 1574, 765, 693, 417, 218, 85
9	7868, 947, 920, 255, 90, 7, 5, 2, 1	3904, 2412, 1253, 757, 687, 529 , 265, 198, 90	4318, 2637, 944, 699, 602, 439, 222, 180, 54
10	7868, 920, 905, 255, 90, 42, 7, 5, 2, 1	2412, 2186, 1718, 1253, 757, 687, 529, 265, 198, 90	3623, 2399, 1018, 856, 667, 626, 359, 248, 214, 85

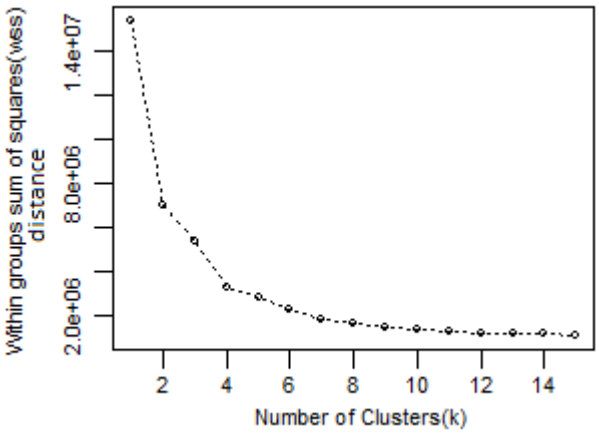


Figure 4.3. Identifying correct number of clusters (*wss vs. k*)

profiles having similar web-browsing ratios of 92.26 %, 83.45% and 77.39% compared to only two profiles with high web-browsing and well-parted usage ratios of 90.04 % and 62.84 % derived by k-means. This trend continued up until the maximum examined value of ten profiles.

To calculate an approximate value for the eps value (ε) to be used in DBSCAN clustering, a k-distance graph was plotted (using k= 'dimension of data D' +1 =9), based on the 8-dimensional application tiers given in Table 4.1 [266]. The relevant 9-NN distance vs data points plot is depicted in Fig. 4.4. The 'knee of the curve' in the graph provides an approximation of the eps (ε) distance to be around 8, 10 or 12. Additionally, as discussed earlier, selection of the second minPts parameter is equally important in dictating the efficacy of the resulting clusters. Therefore, three different

values were chosen to be used with each approximate eps (ε) value. A relatively smaller value of 5 (default in R *dbscan* package) [210] was selected to generate the maximum number of clusters and analyse their respective membership and noise. Afterwards higher values of minPts (minPts $\geqslant$ D + 1) i.e. 10 and 50 were chosen to reduce the total number of clusters and observe the variation in resulting per-cluster membership. The derived clusters for each eps (ε) and minPts combination are given in Table 4.4. As with hierarchical clustering, the DBSCAN clusters depicted in Table 4.4 showed a great deal of over-fitting of data points. For the smaller value of *minPts*=5 or *minPts*=10, for each selected *ε* value, DBSCAN clustering resulted in a large number of clusters (between 7 to 17). However, significant variation in membership distribution of the data points was observed in the derived clusters. While a few clusters comprised the majority of data points, remaining had substantially low membership rendering them meaningless for profiling purposes. Relatively larger value of *minPts*=50, resulted in far fewer clusters (3 to 4). However, it was again noted that either one or two clusters contained the majority of the data points with remaining clusters having minimum membership. The number of outliers for *minPts*=50 was also quite high, ranging between 244-1060, and denoting that a significant number of data points did not associate with any of the derived clusters and were considered as noise. This did not fit well with the earlier stated requirement of reducing outliers to a minimum. Despite using different *minPts* values with each *ε* approximation, the clusters derived using DBSCAN did not therefore present satisfactorily expressive results, when compared to the clusters derived using k-means. The profiles derived using k-means (k=6), in the present case, represented a more meaningful balance catering for both heavy membership profiles as well as lower ones without compromising too much on mutual exclusivity or overfitting of users. The application usage per profile derived using k-means clustering is analysed in the following sub-section.

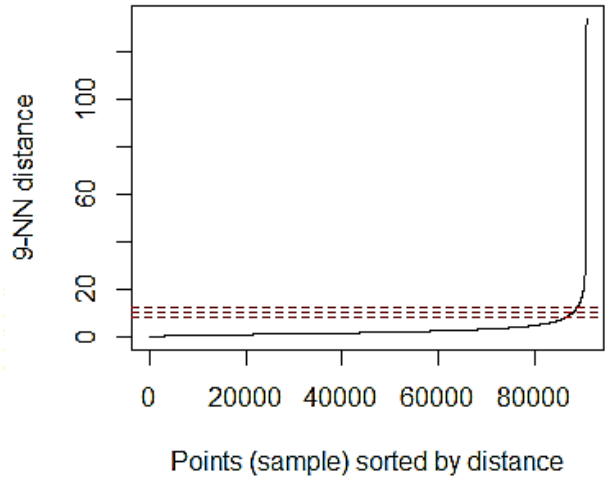


Figure 4.4. K-distance graph (ε- eps estimation)

Table 4.4. Profile Membership Distribution per Cluster (DBSCAN)

# Clusters	ε- eps	minPts	Membership Size	Noise Points
17	8	5	9396, 183, 47, 36, 23, 13, 13, 7, 7, 7, 7, 5, 5, 5, 5, 4, 4	327
10	8	10	9152, 130, 176, 36, 36, 23, 14, 13, 13, 12	490
4	8	50	8169, 621, 132, 113	1060
15	10	5	9530, 186, 51, 37, 23, 13, 13, 9, 6, 6, 8, 7, 6, 6, 4	190
7	10	10	9457, 184, 39, 37, 23, 13, 13	329
3	10	50	9079, 124, 168	724
11	12	5	9621, 195, 74, 28, 19, 17, 11, 6, 5, 5, 3	111
5	12	10	9571, 186, 63, 17, 14	244
3	12	50	9241, 124, 177	553

4.4.2 Results

The application usage distribution for each of the six derived traffic profiles is given in Fig. 4.5. Compared to the profiles derived in chapter 3, the updated design accounting for individual user devices in each customer premises as well as the inclusion of unidentified traffic flows resulted in the addition of two more profiles. The corresponding graphs illustrating per-profile membership and flow statistics over the observed duration are presented in Fig. 4.6 – Fig. 4.7.

Profile 1 concentrated mainly on web browsing (68.92%), with minimal usage of other applications, including downloads (3.46%), streaming (1.29%), communications (1.67%) and significant unknown traffic (8.68%). The devices in this profile may therefore, be summarized as *high intensity web-surfers*. Profile 1 also had the highest number of device membership. Moving on, profile 2 also concentrated on heavily on web browsing, and although the browsing component was significantly higher (>90%) as compared to high intensity surfers, other application usage was minimum, apart from unknown traffic flows (2.06%). The devices in profile 2 could be labelled as *low-intensity web surfers,* having a comparatively lower traffic volume than profile 1 and second highest number of profile membership. Profile 3 also inclined towards web browsing, but traffic distribution among other activities such as emails (2.19%), downloads (3.59%), streaming (1.60%) and games (2.19%) was slightly higher than both *high* and *low intensity surfers*. The unknown traffic flows in this profile were substantial (23.25%). Closer examination of the unknown traffic samples revealed that approximately 57%-59% of traffic flows targeted online gaming servers. Due to their proportional use of many applications in addition to gaming such as communications and streaming, devices in this profile can be categorized under *all-rounders* (or *gamers*). User devices in Profile 4 were heavily

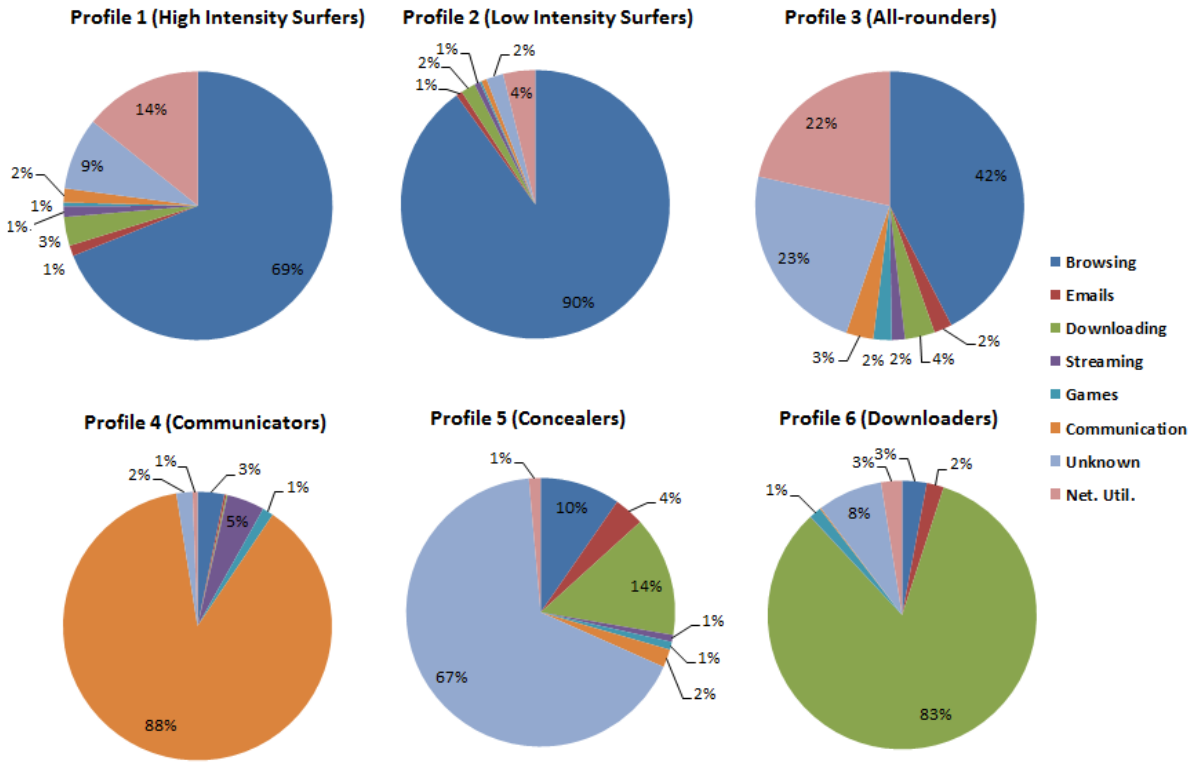


Figure 4.5. User Traffic Profiles

biased towards communication related applications (88.01%), with negligible traffic in any other tier and were, therefore, labelled as *communicators*. Unknown or concealed traffic accounted for most of Profile 5 at 66.92%. The traffic identification scheme discussed earlier fell considerably short of identifying the applications or website visitations for devices in this profile. Closer analysis of source and destination ports revealed that concealing devices were randomly using un-assigned ports with the majority of traffic attributed to P2P applications (approximately 55%). Devices in this category can be categorized as *concealers* or *P2P users* having a major P2P usage profile. Furthermore, due to the low percentage of unidentified application traffic in other profiles in comparison to *concealers*, unknown network traffic did not significantly influence the overall results (other profiles), apart from addition of one new cluster incorporating devices with significant P2P usage. While P2P is most likely to represent background activity, the policing of such a profile within SDN may or may not focus on P2P but on the rest of the traffic generated by the user as determined appropriate by the administrator. Lastly, profile 6 mainly focused on file downloads (83.02%) from the internet using FTP and other download applications and had the lowest number of devices and users. The primary traffic flows in this category used FTP based FileZilla video streaming (server) connecting to user VLC player (client). Profile 6 users could consequentially be names as *downloaders* with a significant online *streaming* component. Since, video streaming may include an underlying rate limit, downloading files via FTP usually have rate bounded only by the

access/uplink speed. To summarize, each device per user premises represented a significant discrimination towards a certain mix of user activity. In the next section, the consistency of device membership in the derived traffic profiles is evaluated to comprehend changes in user behaviour in terms of their respective device usage.

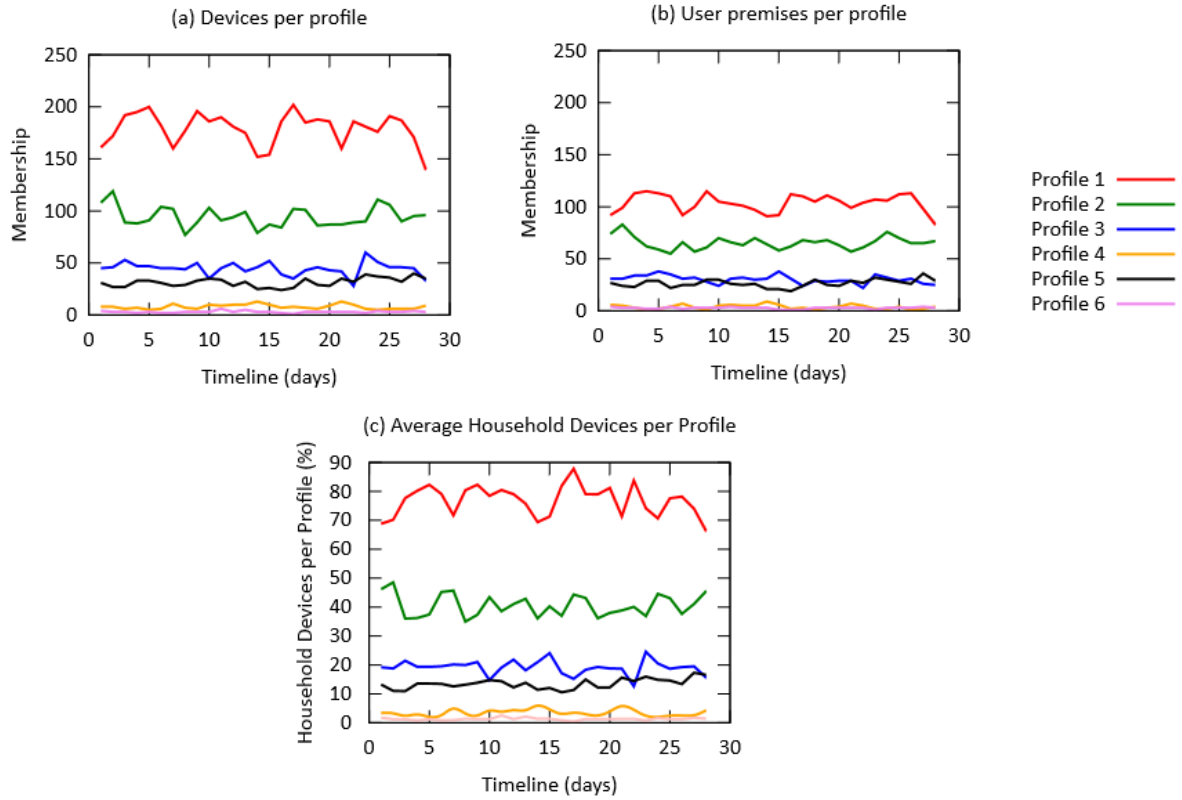


Figure 4.6. (a) Number of devices per profile, (b) Number of User premises per profile and (c) Averange household devices per profile

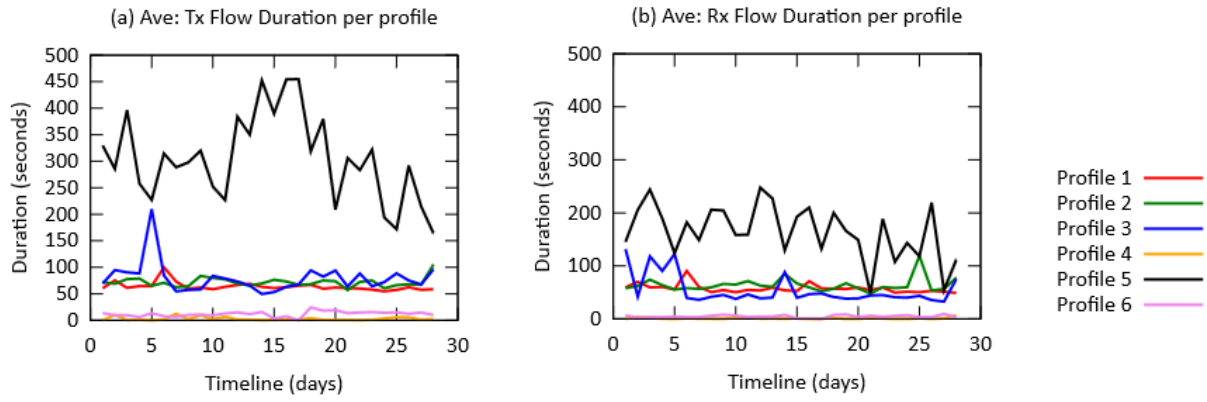


Figure 4.7. (a) Average duration of transmitted flows and (b) Average duration of received flows

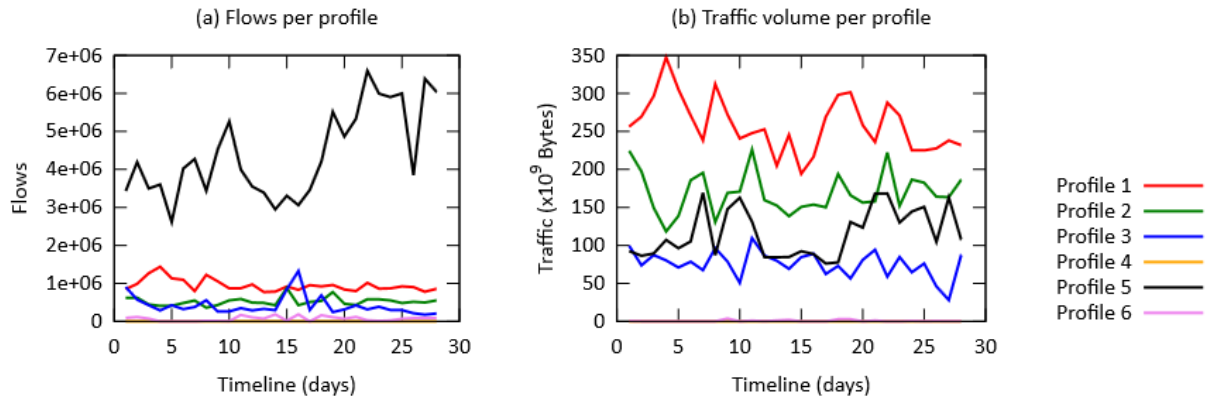


Figure 4.8. (a) Total number of flows per profile and (b) Total data volume per profile (Bytes)

4.4.3 Profile Consistency

Profile consistency emphasises the importance of gaining a better insight to changes in user activity per device as well as requirements or frequency for re-profiling. A user that browses for one hour on a particular day might be clustered in a different profile if using a range of applications for a much longer duration (e.g, 10 hours) on a different day due to bigger overall traffic/activity. To determine the number of devices per profile and their mutual correlations, the Pearson's correlation coefficient [190] was used with the results given in Fig. 4.9. A negative correlation co-efficient would indicate an inverse relationship with one profile gaining more devices and the other losing, however, not necessarily among the same profile pairs. Positive values refer to an increase in devices for both pairs. Values closer to zero represent no meaningful relationship, translating for minimal increase or decrease in devices per profile pair. As shown in Fig. 4.6, there is a blend of both negative and positive correlations representing changes in number of devices per profile. Using Fisher's transformation, the average value of correlation co-efficient was calculated to be -0.0931 [191]. The relatively low average indicates no significant change in device numbers per profile, with a slight bias towards an inverse relationship between each profile pair. To further evaluate, the user device profile retention, the average probability of change in device profiles per subsequent day of study was computed and is given in Table 4.5. *Downloaders* showed the highest consistency in retaining profiles at 97% while *all-rounders* showed lowest at 81%. The probability of a profile gaining or losing a device every 24 hours is also highlighted in Table 4.5 The *downloaders* had the highest probability of gaining a device (60%) with *high intensity web surfers* having highest probability of losing a device (59%).

Where devices did change profiles, the average probabilities of inter-profile transitions every 24 hours are given in Table 4.6. It was observed that where devices transitioned to a different profile, it was always to profiles having somewhat similar application usage ratios to their own. For example, *low surfers* would transition to *high surfers* (8%) compared to other profiles. *Concealers* did not show any significant change in profile, except to *all-rounders* which was also quite minimal (5%). This further emphasized the fact that majority of devices within this group more closely followed an application dictated pattern of behaviour mainly due to P2P activities. *Downloaders* seldom changed profiles highlighting that the small number of devices in this profile were also being dedicatedly used for streaming videos from the internet-based servers. Hence, where there was a transition observed among the traffic profiles, it was only due to variation in the same user activity rather than a complete change of role per device. Users, therefore, continued to use the same devices for same kind of activity albeit in varying proportions rather than showing drastic changes in their normal routine.

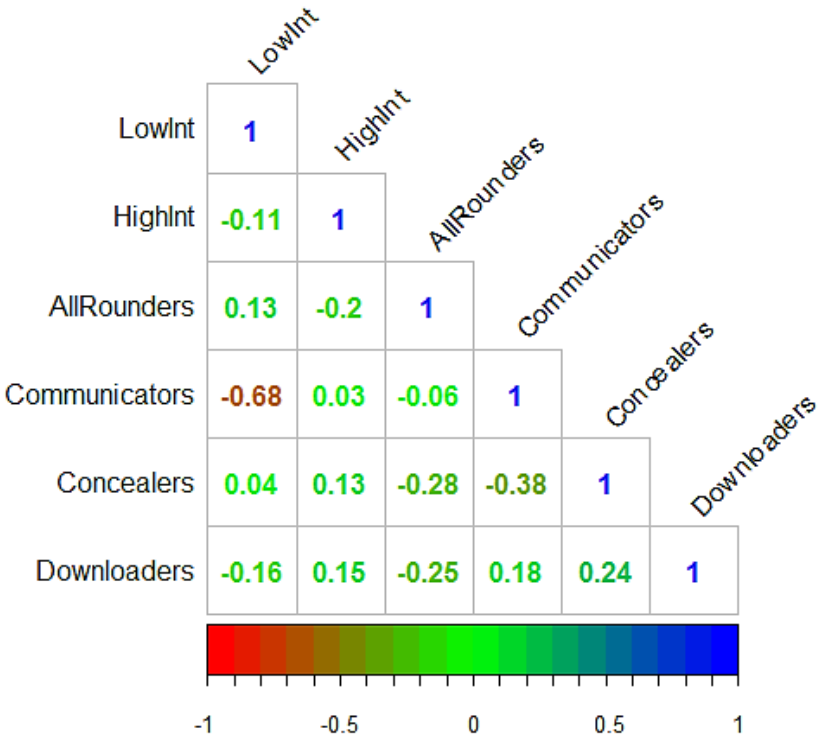


Figure 4.9. Pearson Correlation Co-efficient between Device Profiles

Table 4.5. Average Probability of Profile Change (/24 Hrs)

User Profiles	Probability of No Change	Probability of Change		
		Change	*Prob. Device Gain*	*Prob. Device Loss*
H. Int Surfer	0.87	0.13	0.40	0.59
L. Int Surfer	0.88	0.11	0.46	0.53
All-rounder	0.81	0.18	0.42	0.57
Comms.	0.84	0.15	0.57	0.42
Concealers	0.87	0.12	0.48	0.52
Downloaders	0.97	0.03	0.60	0.40

Table 4.6. Average Probability of Inter-Profile Transition (/24 Hrs)

User Profiles	High Int. WS Surf	Low Int. WS	All-rounders	Commmunicators	Concealers	Downloaders
High Int. WS	0.87	0.08	0.03	0.0015	0.007	0.001
Low Int. WS	0.08	0.88	0.01	0.01	0.008	0.002
All-Rounders	0.11	0.03	0.82	0.003	0.032	0.0005
Communicators	0.09	0.06	0.05	0.84	0.001	0.001
Concealers	0.03	0.03	0.05	0.0006	0.87	0.002
Downloaders	0.0005	0.001	0.0001	0.0004	0.0005	0.97

4.5 Effective network management in residential SDN

The derived traffic profiles showed a high level of consistency in terms of membership numbers. Hence, once the traffic profiles have been derived based on application usage ratios, the baselines of network traffic per profile as depicted in Fig. 4.6 - Fig. 4.7 provides an intuitive means to monitor the residential network. Daily aggregate traffic can be effectively examined by analysing value changes in traffic metrics per profile with any anomalies serving as an advisory to trigger a re-evaluation of profiles and identify network abnormalities. For end users wanting to better manage their data usage, service providers may employ traffic profiling to place users into correct subscription models while also providing them with their daily traffic projections through service provider portals or customer home gateways.

Traffic profiling therefore, provide administrators with enhanced capability to monitor network activity and update capacity based on anticipated user behaviour for achieving better quality of experience. It may also aid in protecting users from security threats or in enforcing policies. For example, in the present case concealers (P2P users) either could be rate-limited or blocked by making provisions in the individual customer routers shown in Fig. 4.2 to enforce the underlying network usage policy.

Furthermore, despite growing Internet speeds, the last mile access infrastructure of the service provider remains a source of network contention due to an ever-increasing range of greedy, bandwidth demanding applications. By using an SDN based traffic engineering framework between the residential gateway and the service provider, provisions may be made that allow residential users to prioritize certain user profiles within their network to better manage the last mile bandwidth. The utilization of policy primitives that dictate the distribution of available bandwidth among different profiles, may allow fine-tuning the resource (bandwidth) allocation among multiple residential users with relative ease. The next chapter presents an SDN based traffic management application to this effect.

4.6 Conclusion

The present work focused on profiling multi-device user traffic in a residential network based on application usage using three different analysis techniques i.e. k-means, hierarchical and DBSCAN unsupervised clustering. The profiles derived using k-means presented a more meaningful view of application usage among different classes. The six unique user profile extracted were further benchmarked every 24 hours to ascertain their stability. Over the four-week observation period, the analysis indicates that the number of users and devices per profile remained fairly consistent. Any inter-profile transitions were mainly due to proportional variation in same kind of user activity triggering a device profile change (to a somewhat similar profile in terms of application usage). The overall high rate of profile consistency reported even in this multi-device environment enhances the feasibility of validates using the extracted profiles for effective network management and defining and implement network policies.

Despite recent improvements in the Internet broadband speed, residential users often experience bandwidth contention, especially when several users are simultaneously using bandwidth intensive applications. As a test case, the following chapter utilizes the extracted profiles in a custom designed SDN application to effectively manage the residential network. The framework allows residential users to create network policy primitives which define the bandwidth allocation priority among different user profiles when several users are simultaneously connected to the Internet. The application is tested in a simulation environment to validate the employability of traffic profiles in residential based SDN for network monitoring and management purposes.

Chapter 5 User-Centric Residential Network Management

5.1 Introduction

Residential networks are getting increasingly difficult to manage due to the ever-growing number of devices, diversity in application usage and evolving traffic patterns of end users. A typical residential network incorporates several end user devices sharing the same Internet connection, each with varying application usage [192][193]. Despite a substantial increase in internet uplink and downlink speeds [194], managing uplink and downlink bandwidth, a finite resource, among several users in the same premises is a challenging task [47][49][107]. Changing traffic patterns in residential networks may require repeated manual interventions to adjust policies at the residential router to satisfy individual user requirements, coupled with the fact that there is seldom a clear understanding of the application usage mix of all users to correctly implement user based rate-limiting or bandwidth capping [195]. Real-time re-programming provided by SDN may significantly improve flexibility in resource management inside the service provider's network [51], but equally important is the effective allocation of resources for users residing towards the edge, more specifically users inside the residential network. Prior studies such as [49], proposed virtualization of residential gateways and their inclusion into the service provider SDN framework for simplifying administration. Other approaches suggest reactive traffic shaping based on performance monitoring of data retrieved from residential gateways and managing bandwidth usage by allocating data usage caps to each device [107]. While this reduces the burden of residential network management from the end user, such an arrangement also raises user privacy concerns and presents scalability issues for the service provider SDN controller in managing routers for individual end users. To allow greater user control over their network, Mortier et al. in [47] proposed a similar strategy leveraging SDN technology for managing residential routers while Chetty and Feamster in [195] argued for better user interfaces allowing users to accurately set up network policies based on usage quotas. Existing approaches of controlling network congestion through dynamic queue management in both SDNs and legacy networks look promising in mitigating latency and packet loss at the application level [197-199].

The refactoring of the residential network through abstracted high level policy based management via a software defined networking framework although appears to be a viable choice [47][49][51][52][196], it raises prioritization issues to determine which user devices to cap and what applications to expedite. As identified in chapter 4, per user application usage ratios may vary

significantly within residential networks. Employing the default method of flow metering specific applications to control forwarding constructs in SDNs or using advanced congestion control adaption schemes such as active queue management [197-199], to better manage packet queueing may fall short of satisfying individual user requirements in terms of real-time resource allocation.

In this context, it is vital to understand the users' behaviour inside the residential network to accurately define and apply any such resource allocation policies in the first place. Instead of using individual applications, user traffic profiling can be used to derive different user classes present in the network on the basis of actual application usage while also providing an estimation of per-profile bandwidth consumption to achieve better traffic management schemes catering to all users [200]. As previously discussed in chapter 3 and chapter 4, user traffic profiles may be derived based on the percentage of generated flows (NetFlow records) per user for each pre-defined application tier and further subjected to unsupervised k-means clustering to derive unique user traffic classes. Characterizing network workload using per-user application distribution ratios (user profiles) accurately expresses user activities and aids in implementing user-centric traffic engineering solutions. The present chapter, therefore, proposes and develops a dynamic queueing based user-centric traffic optimization scheme utilizing the extracted user traffic profiles and user defined profile priorities to effectively manage the allocated downlink and uplink bandwidth among several users in a residential SDN. As part of the validation phase, an SDN application is designed for allocating per profile bandwidth among residential users, and tested in a Mininet based simulation environment under different traffic scenarios to evaluate its effectiveness.

The remainder of this chapter is organized as follows. Section 5.2 details the traffic management design, highlighting user profile prioritization and the queue assignment algorithm for per-profile resource allocation. Section 5.4 evaluates the proposed design and resulting improvements, and conclusions are drawn in Section 5.5.

5.2 Design

The user-centric traffic management design proposed in the present chapter employs a Ryu SDN controller [30] supporting OpenFlow architecture [17] and utilizes egress QoS queueing for rate-limiting per-profile traffic and allocating of link capacity to individual user flows. The design comprises of two components (i) a profile derivation framework and (ii) an SDN based traffic

management application. The details of each component are further discussed in the following sub-sections.

5.2.1 Profile derivation framework

Due to their scalability of use, NFV and SDN technologies such as Open vSwitch as well as many vendor hardware switches and OpenFlow ports on other platforms (OpenWRT, Pantou, etc.) support flow-based monitoring and are capable of exporting NetFlow logs [48]. As previously discussed in chapter 4, NetFlow can be used to derive user traffic profiles based on the percentage of generated flows per user for each pre-defined application tier and further subjected to unsupervised k-means clustering to derive unique user traffic classes. Applications can be identified using destination webserver IP addresses or using other Layer 7 classifiers. A typical residential router is, therefore, able to export NetFlow logs either by default or by operating system updates. The resulting flow records can be cluster analysed internally in the residential gateway (provided an enough memory and CPU resource is available) or exported to an external server for profile derivation, which may also act as the network attached SDN controller.

An architectural view of the profiling engine designed based on studies in earlier chapters for deriving profiles of user devices connected to the residential gateway of an OpenFlow capable switch (e.g. OpenWrt) [15][17][200] is given in Fig. 5.1 [Appendix – 2.4]. Individual applications can be identified using reverse DNS lookup on destination webserver IP addresses or other Layer 7 classifiers. The resulting profiles are stored and continuously monitored with any flight from benchmarked baselines triggering re-profiling.

5.2.2 Traffic management application

The traffic management application employs the Ryu SDN framework. Ryu provides several software modules with well-defined APIs making it possible to create real-time network monitoring and control applications with ease [30]. The controller component has built-in support for managing network devices, using the popular southbound OpenFlow protocol. The Ryu framework provides three primary methods for QoS prioritization of flows: ingress policing of incoming flows via rate-limiting, egress traffic shaping by associating outgoing flows to assigned queues and lastly by meter tables [17]. The first two schemes have been implemented in OpenFlow compatible switches such as the Open vSwitch [86]; however, meter tables, although a part of the OpenFlow

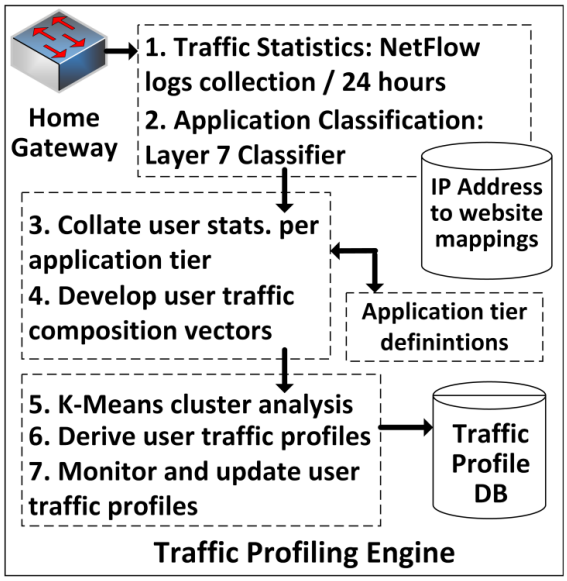


Figure 5.1. Traffic Profiling Engine

specification, have not been enabled in Open vSwitch, with only a few vendor hardware switches supporting their use. To keep the proposed approach applicable to all software switch variants, the present work primarily used egress QoS queueing to rate-limit per-profile traffic.

The traffic management application follows a two tiered approach as shown in Fig. 5.2. To make provisions for Linux HTB functionality [202], the standard layer2 Ryu switching application is modified to support the retrieval and submission of HTB QoS rules per switch by using RESTful calls to the controller [Appendix – 5]. The SDN controller is, therefore, able to assign HTB queues dynamically for each switch-port as required without manually adjusting these on each port individually. The number of active Internet user connections is monitored by using a real-time flow count threshold per switch-port. Any change in user connections is communicated by the switch-port monitoring module to the queue calculator. Based on the user-defined profile priorities and the current as well as predicted traffic per profile, the queue calculator computes the optimal queue rate per user. The computed queues are thereafter, applied to the residential router uplink and the service provider gateway downlink interface via the controller and the process is iterated tracking the number of real-time user connections. The application aims at managing the last mile bandwidth between the residential router and the service provider gateway through the residential SDN controller, using a typical residential broadband budget (e.g. up to 2Mbps upstream and 20Mbps downstream) when the total bottleneck bandwidth is higher or lower than the sum of the clients.

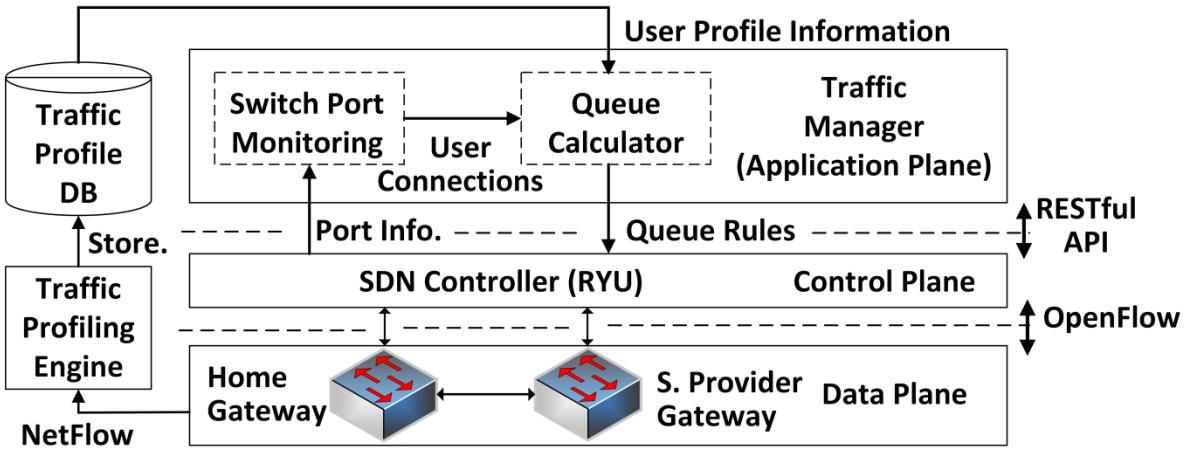


Figure 5.2. Traffic Monitoring and Control

5.2.3 Test Profiles

In order to ensure that the proposed method matches a real network scenario, the present study utilized profiles derived earlier in chapter 4, from a residential network housing approximately 250 user premises. The unknown traffic flow component for each derived profile was accounted using offline destination IP and port address analysis. User profiles and traffic statistics were accordingly updated. Identification of unknown traffic (z), merging of browsing (w) and Email tiers (e) resulted in the application tiers being reduced to five to better reflect the user activities. Fig. 5.3 summarizes the application usage for each profile as a percentage of user generated flows. Profile 1 concentrated mainly on web browsing (85%) with limited usage of other applications and remained as *high intensity web-surfers*. Profile 2 also concentrated on web browsing (95%); however, with extremely limited usage of any other application and also lower data usage as compared to high intensity surfers, hence users in this profile were called *low-intensity web surfers*. Profile 3 inclined towards online video streaming via FileZilla FTP server, and traffic distribution among other activities (emails, downloads and games) was relatively lower than both *high* and *low intensity surfers.* These users were therefore, accordingly named *streamers*. User devices in Profile 4 heavily tilted towards using communication related applications (88%), and therefore, labelled as *communicators*. Online games traffic accounted for most of Profile 5 at 60%. Users in this profile were categorized as *gamers*. Profile 6 mainly focused on downloading using P2P clients. A substantial proportion of traffic flows in this profile comprised of unknown traffic that was attributed to P2P usage (55%), as examined earlier in chapter 4 and, therefore, named as *P2P users* in the present work. Additionally, to account for guest users, representing one-off network users or users not having any statistical usage information for profile derivation, a *guest profile* was created. Table 5.2 represents the average upload and download rate per profile and total data

consumption every 24 hours. *Streamers* had the highest average data transfer rates having 270kbps upstream and up to 6300kbps downstream. This was followed by *P2P users* and *communicators*. *Low intensity web surfers* accounted for lowest data rates at 75kbps upstream and up to 175kbps downstream per user. Hence, the average data rates varied for each user category with some users such as *low intensity web surfers* only consuming a small proportion of bandwidth compared to others and residential users may want to prefer certain user categories over others when multiple users are connecting to the internet and simultaneously competing for bandwidth.

5.2.4 Setting User Profile Priority

Traffic congestion in residential networks can cause performance degradation for users even with a decent speed connection depending on other users' activities [203][204]. The derived user traffic profiles provide residential users with a useful insight into the mix of user classes, their application trends and resource consumption to help alleviate network management difficulties. To give the residential users control over which users to prioritize in terms of bandwidth allocation the proposed policy language uses a prioritization value associated with each derived profile to coordinate the challenges of managing shared network bandwidth. Table 5.1 depicts a sample priority level for queue assignment and the corresponding required data transfer (queue) rates per user. *Low-intensity web surfers* (with minimal bandwidth footprint) have been allocated the highest priority while *guest users* are allotted the lowest priority and placed in the default root queue (q_0). However, this is to be used as an example and the priority policy can be set by the home user on demand. The profiles may be further benchmarked for stability and continuously monitored, with any deviation from baseline values triggering re-profiling using the automated traffic profiling engine/ script [Appendix – 2.3]. The traffic management scheme, therefore, removes the burden of continuously reconfiguring the network from the user with input required only following any profile re-evaluation or priority updating. As evident from the Table 5.1, depending on number of user connections, only a subset of profiles (in order of priority) may be allocated their required upstream and downstream data (queue) rates. The subsequent queue calculation algorithm for this purpose is detailed in the next section.

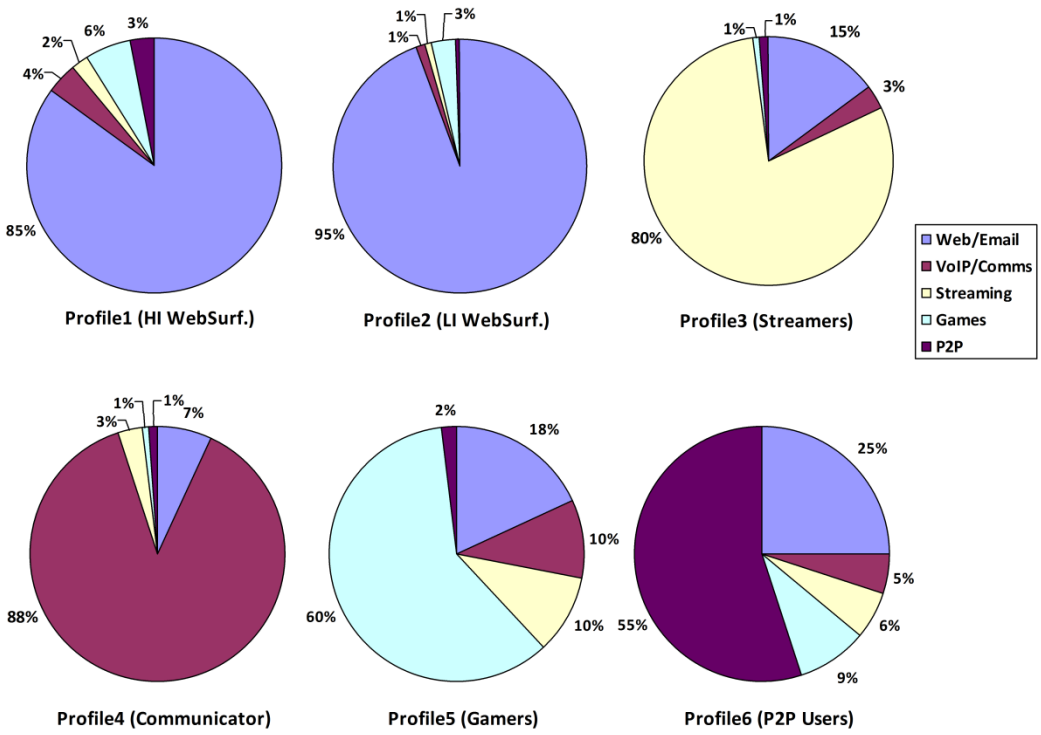


Figure 5.3. User Traffic Profiles

Table 5.1. Average Data Transfer Rates and Sample Profile Priority Level

User Profile (i)	Avg. Data Transfer Rate (kbps)|| Queue (μ)		Protocol Ratio TCP: UDP	Data vol./24 hours (GB)	Sample Priority Level
	Up.	*Dn.*			
WebSurf (L)	75	175	3:2	0.05 – 1.1	1 (High)
WebSurf (H)	300	500	3:2	0.15 – 1.42	2
Comms.	500	650	5:1	0.3 – 2.1	3
Streamers	270	6300	2:1	1.9 – 3.5	4
Gamers	400	500	1:4	0.25 – 1.8	5
P2P Users	1450	2000	8:1	1.5 – 3.9	6
Guest Users	def:q0	def:q0	-	-	7 (Low)

5.2.5 Queue computation and re-evaluation

The queue assignment algorithm follows the bandwidth division and re-allocation approach given in Fig. 5.4(a). If the sum of required queue rates μ of n connected users from all m profiles is less than or equal to the respective available uplink or downlink bandwidth ($\Sigma_{i=1,m}\ \Sigma_{j=1,n}\ \mu_{ij} \leq \beta$) then all the users are allocated their required queue rates as given in Table 5.1. If however, the available bandwidth is less than the sum of required user bandwidth, queues are assigned based on the

user's profile priority and for multiple users from the same profile on a first come first serve basis. Once the total available bandwidth has been allocated any remaining users (profiles) are allocated the default queue (q_0). Despite using the HTB primitive (performing hierarchical rate distribution among configured queues), per-profile queue re-evaluation is required to accommodate changing real-time profile memberships and to resolve the resulting bandwidth contention in an optimal fashion. To reduce the subsequent SDN controller management overhead, queue re-evaluation triggered by an update to user connections only requires the flows (queues) of the respective profile and any subsequent users in lower priority profiles to be updated. As depicted in Fig. 5.4(b), addition or deletion of active users in profile *k* will result in queue re-assignment of profiles *k*, *l* and *m* leaving pre-installed flows of profile *i* and *j* in force.

```
m = number of profiles, n = number of users per profile,
β = uplink || downlink bandwidth
μ_ij = required queue rate per user j for profile i
q_ij =assigned queue rate per user j for profile i, q_0 = default root queue

if [Σ_{i=1,m} Σ_{j=1,n} μ_ij ≤ β ]
    all n users per profile i are allocated their required queue rates;
end if

else
  for (i=1; i≤m; i++);
    for (j=1; j≤n; j++);
      if β ≥ μ_ij
        q_ij += μ_ij;
        β = β - q_ij;
      end if
      else
        ∀ q_i = q_0;
      end else
    end for
  end for
end else
```

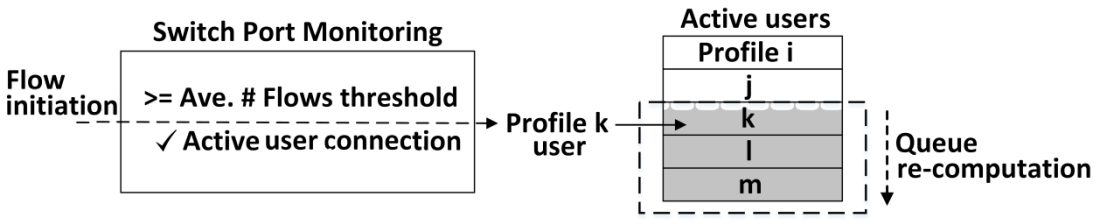


Figure 5.4. (a) Queue calculation algorithm and (b) re-evaluation schedule

5.3 Evaluation

The proposed design was evaluated on the profiles depicted in Fig. 5.3 using Mininet topology which is shown in Fig. 5.5, and Ostinato software was used for traffic generation [103][205]. The network comprised 10-18 user machines and 5-10 web servers added at different stages to observe variation in traffic statistics, along with two switches (s1 and s2) representing the home-gateway and ISP side router [Appendix – 4.1]. To model an average broadband connection, the effective uplink and downlink bandwidth between the home gateway (s1-eth1) and the Internet service provider (ISP) edge (s2-eth1) were limited to the maximum of 2Mbps and 20Mbps respectively using the root queue class (q0) on the respective interfaces. The flow threshold was set to one flow per user in the simulation to identify active Internet users. In order to comparatively test the impact of the traffic management algorithms, the following three scenarios were sequentially enabled.

1) When the sum of client transfer rates both upstream and downstream was less than the service provider allocated budget, i.e. 2Mbps upstream and 20Mbps downstream [0:tA].
2) When upstream data transfer rates exceeded the uplink bandwidth and downstream was within assigned limit [tA:tB], and
3) When both upstream and downstream data rates were breached causing congestion at both ends of the service provider to residential gateway link [tB:tC].

The relevant time intervals and user connections for each scenario are given in Table 5.2. Iperf utility was used to measure the TCP bandwidth from the user clients to the servers over each time interval. To gain packet loss information Iperf UDP tests were done between the users and web servers over the same intervals while network latency (RTT) was measured by observing PING responses.

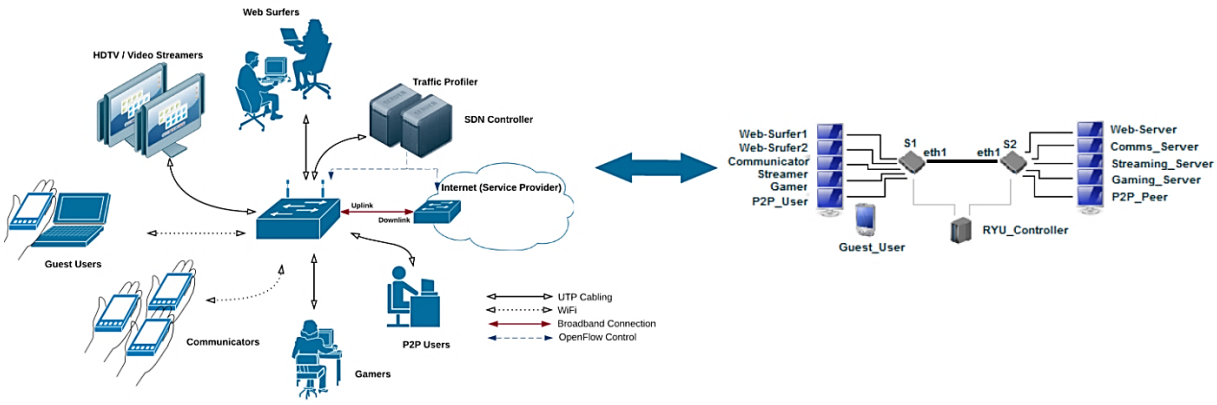


Figure 5.5. Mininet Home Network Topology

During [0:tA], users were randomly selected from different profiles such that the sum of their upstream and downstream traffic remained within the budget. For a total of five users, the total uplink and downlink traffic was 1.550Mbps and 8.125Mbps respectively. As given in the Fig. 5.6, the packet loss and network latency observed per profile during [0:tA] was minimal regardless of variation in individual data transfer rates per user. However, with a P2P user connecting to the internet during [tA:tB], the upstream transfer rate of 2.7Mbps exceeded the allocated bandwidth causing reduction in average bandwidth per user (0.465Mbps) and increase in both the packet loss (12.52%) and the latency (275ms). Addition of more users during the time interval [tB:tC] resulted in traffic on the downstream (25.875Mbps) also exceeding the allocated bandwidth causing both downstream and upstream link congestion and a further decrease in available bandwidth (0.035Mbps) per user with a corresponding spike in the packet loss (49.93%) and latency (525ms). As a minimum requirement for maintaining good link quality, the packet loss should not go over 1%. A high packet loss rate results in the generation of a lot of TCP segment retransmissions which will in turn affect the bandwidth. During the total duration [0:tC], as long as data transfer rates remained within available bandwidth i.e. [0:tA], there was minimal packet loss and latency per user regardless of the number of connections and a traffic management scheme was not needed. However, in instances where either the uplink or downlink bandwidth was breached, a substantial decrease in per user bandwidth and an increase in packet loss and latency were observed. The absence of a traffic management framework in such cases required all users to compete for last mile bandwidth resulting in high packet losses and latency despite the nature of their online activity or how crucial it may be from an end user's perspective.

Table 5.2. Traffic Generation Scheme

Time Seq.	Connected Users	Uplink Traffic (Mbps)	Downlink Traffic (Mbps)	Avg. pkt. loss/ user	Avg. BW / user (Mbps)
0:t_A	1 High Int web surfer 1 Low Int web surfer 1 Communicator 1 Streamer 1 Gamer	1.550	8.125	0%	1.464
t_A:t_B	+ 1 P2P User	2.700	10.125	12.52%	0.465
t_B:t_C	+1 Streamer +1 Communicator +1 P2P User +2 Guests	5.500	25.875	46.23%	0.035

To evaluate the results of dynamic bandwidth allocation based on user-defined profile priorities employing the proposed design, it can be assumed that the residential network chooses to prioritize traffic as per the profile priority table depicted earlier in Table 5.1. This would accord *low intensity web surfers* highest priority and *guest users* the lowest. The priority table is however, an example and the end home user can set a different priority policy as required. The uplink queue assignments required to balance the uplink bandwidth among eleven connected users (between 0:tC), based on their respective profile priorities are given in Table 5.3. The first four profiles were allocated their required queue rates. For one *gaming user* requiring 400kbps and two P2P users requiring 2900kbps, however, the remaining bandwidth β = 35kbps, was insufficient and these user profiles along with guest users were, therefore, allocated the default queue on the uplink interface. Limiting upstream traffic from residential router is relatively inconsequential in controlling the

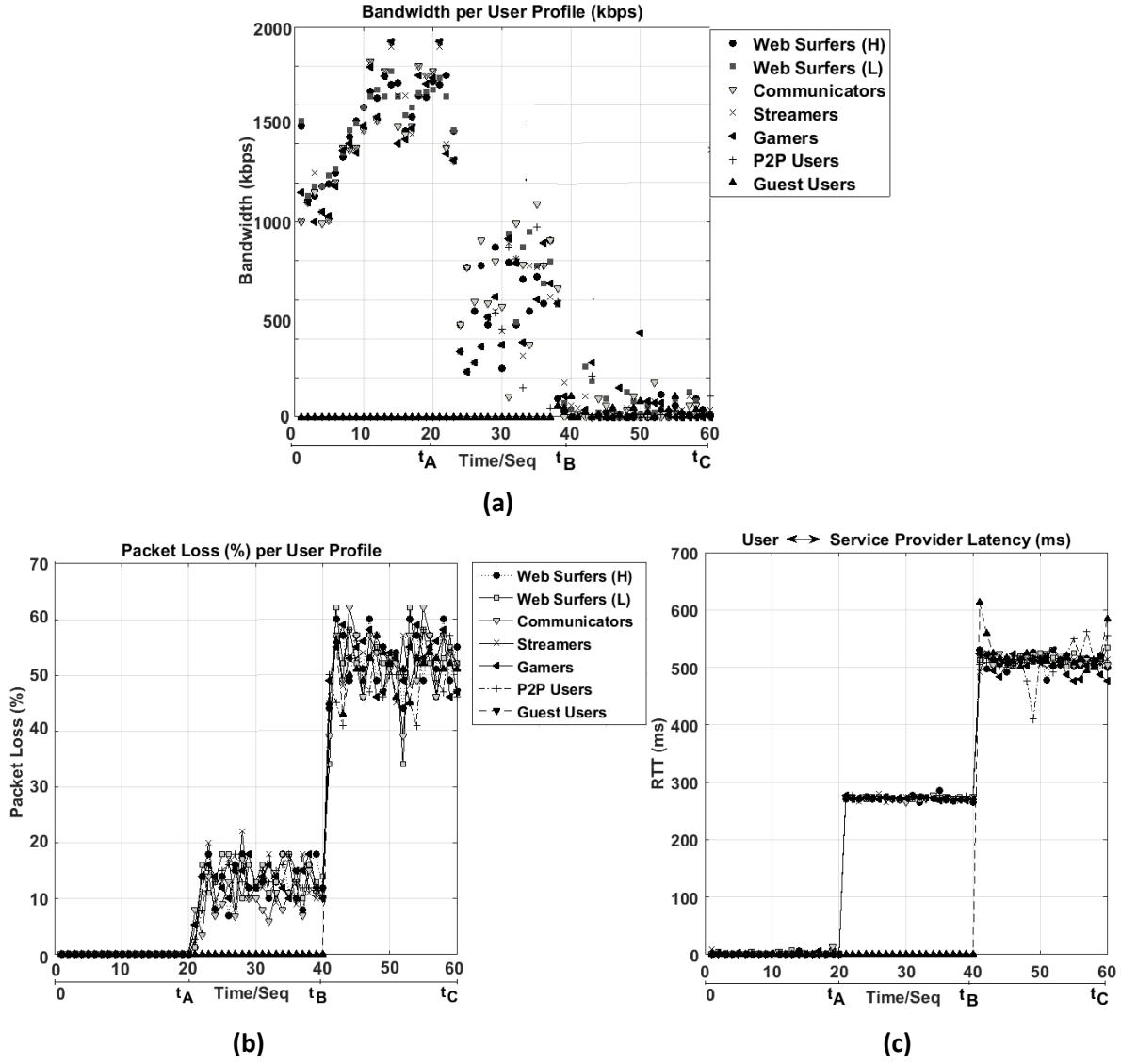


Figure 5.6. (a) Available Bandwidth (b) Packet Loss (%) and (c) Network Latency per User Profile

downlink congestion from the service provider's gateway requiring additional downlink control. Any Ingress policing at the residential router's uplink interface is also relatively insignificant as by the time packets arrive there from the provider side, the last mile bandwidth has already been consumed and dropping packets might lead to further congestion, for example by generating more repeat requests in the case of TCP traffic. En-queueing traffic per profile at service provider downlink interface, however, may more effectively mitigate downlink saturation. To implement downlink queues, a separate control queue may be created to facilitate in-band OpenFlow communication between the residential SDN controller and the service provider router. The service provider's centralized controller(s) may employ customer identification schemes such as VLAN tagging and a dedicated in-band TLS control channel (to accommodate security implications of the control delegation), and authorize residential SDN controller in managing the OpenFlow compliant service provider downlink (switch port) interface leading to additional bandwidth control for residential users [49]. In accordance with the profile priority given in Table 5.1 earlier, a scheme of downlink queue assignments per user profile is also given in Table 5.3. The uplink queue assignments also remain in force. The sum of download data rates for all eleven users (19.075Mbps) was less than the downlink budget (20Mbps). Hence, all user profiles were allocated downlink queues according to their required average download rates with the exception of *guest users* who were placed in the default queue. The corresponding changes in average bandwidth, packet loss and latency for each user profile after uplink and downlink queue assignments [t_C:t_D] are given in

Table 5.3. Uplink and Downlink Queue Assignments [T_C:T_D]

Sample Priority	**Usert traffic profile**	**User membership**	**Req. BW per user (kbps)**		**Queue Assignments (kbps)**	
			Uplink	***Downlink***	***Uplink***	***Downlink***
1	**Low Int web surfers**	1	75	175	q1:75	q1:175
2	**High Int web surfers**	1	300	500	q2:300	q2:500
3	**Communicators**	2	500	650	q3:1000	q3:1300
4	**Streamers**	2	270	6300	q4:540	q4:12600
5	**Gamers**	1	400	500	q0:400	q5:500
6	**P2P Users**	2	1450	2000	q0:2900	q6:4000
7	**Guests**	2	-	-	q0:Def.	q0:Def.
-	**In-band Control**	-	50	-	q_{CTRL}:50	-

Fig. 5.7. Due to guaranteed queue rates, the available bandwidth per profile was more consistent as shown in Fig. 7(a), resulting in reduced packet loss for higher profile users. Users in profiles 1-4 were no longer competing for shared bandwidth but remained within their allocated queues. At the lower end, profiles such as *gamers* experienced higher packet loss than the first four profiles due to having default queue allocation on the uplink. Similarly, other profiles without committed uplink queues such as *P2P users* having high data rate requirement, the average available bandwidth on the uplink did not improve. However, allocation of dedicated downlink queues and reduced bandwidth deviation, resulted in reduced packet loss (11%) and latency (300ms). For two *guest users* having a *streamer* and *gamer* profile (data transfer rate) respectively, the latency increased to 750ms due to further reduction in available bandwidth in the default queue and inconsistent data transfer rates on the uplink as well as downlink.

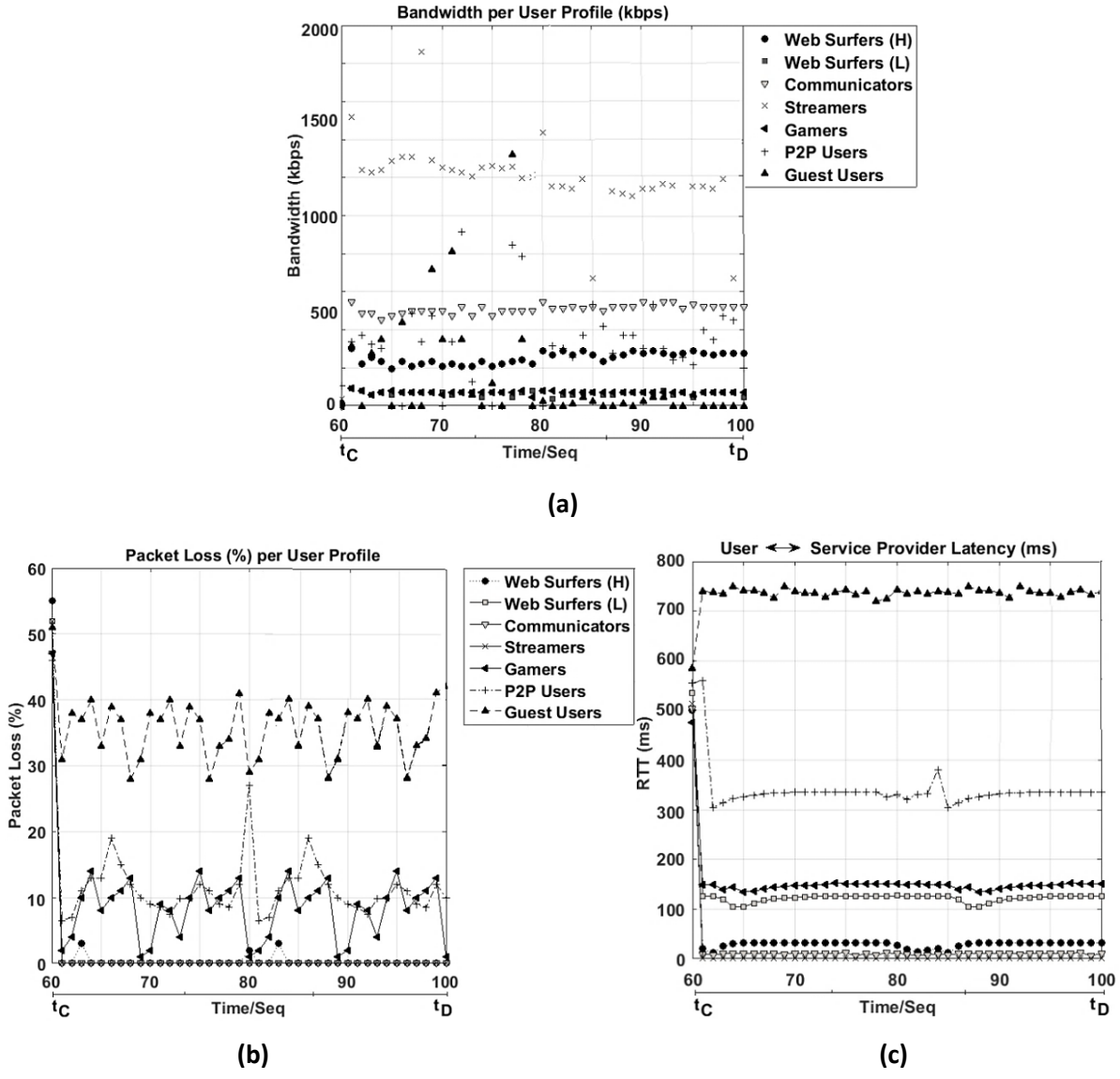


Figure 5.7. (a) Available Bandwidth (b) Packet Loss (%) and (c) Network Latency per User Profile

5.3.1 Discussion

Prior to enabling the queue scheduling algorithm, light web users suffered approximately 15% of UDP packet loss and average bandwidth fluctuated from 800kbps to 200kbps during [t_A:t_B] almost similar to other profiles. The adaptive nature of many applications, the vast majority of which (including streaming etc.) use TCP would mean that such inconsistent bandwidth range and high probability of packet loss would lead to substantial TCP segment re-transmissions and the light web users would struggle to see web pages. Adequate queue bandwidth allocations that take user profiles with typical traffic requirements into account can benefit the performance of high priority users witnessed during [t_C:t_D]. Additionally, the queue scheduling algorithm ensures that any further addition or disconnection of users, for example, beyond [t_C:t_D] only results in updating of assigned flows to the respective user profile and any users in lower profiles as per the hierarchy given in Table 5.1, minimizing queue management and associated computational overhead. While the residential router without having an SDN controller in place could also measure RTT etc. and then apply a scheduling algorithms such as HTB by itself to the individual flows going through it, this would only allow upstream traffic management on the uplink. Implementing a queueing scheme employing OpenFlow protocol and SDN architecture allows controlling bandwidth of application flows based on user's profile from both the residential router and the service provider gateway. Additionally, in contrast to previously proposed approaches of the ISP SDN controller steering millions of residential gateways raising significant scalability and user privacy concerns. Having residential-based SDN controller ensures that profiling and queue computations are done locally. An in-band OpenFlow channel from the controller is responsible for directly updating flows in the service provider downlink interface thereby, reducing ISP controller workload.

5.3.2 Perspective on additional controls

The derived user traffic profiles and the SDN traffic management application designed can be put to use to apply additional controls both in terms of time of the day usage as well as total data usage per profile on a monthly by users at home. Several priority tables similar to Table 5.1 can be constructed in order to prioritize traffic for a different profile of users. For example, to give streamers or gaming users more bandwidth allocation later in the day, the relevant profile priority can be moved up via the traffic management application at a specified time and then re-adjusted again during the day. Additionally, the switch monitoring application may monitor and profile the total data usage per user, then implement further automated rate-limiting for certain user profiles

to avoid going beyond the total allocated data package. The real-time programmability offered by the SDN framework therefore, allows network policy controls at a much more granular level compared to the relatively stagnant control primitives used at present in residential networking.

5.4 Conclusion

The present chapter evaluated the use of a dynamic queue rate calculation and implementation mechanism for efficiently distributing last mile bandwidth between multiple residential users using profile priority levels. Instead of using a per-application rate-limiting approach the proposed profiling scheme accounted for a user-centric mix of applications to facilitate meaningful controls for the end users using an SDN framework. Utilizing user-defined profile priorities for bandwidth allocation through hierarchical token bucket queue assignments at the residential and service provider gateway resulted in a significant improvement in packet loss and network latency for selected high priority users during simulation tests. Compared to previously proposed approaches of integrating SDN controllers on the service provider side driving millions of residential gateways, the present work evaluated the use of a local profiling engine and controller incorporated in the residential network itself offering greater design scalability. The chapter also proposed some additional controls, such as temporal profile priorities and data usage allocations per profile that may be implemented to allow residential users more control over their network usage.

The work so far has discussed the derivation of user traffic profiles in residential networks, investigated a SDN based traffic engineering framework utilizing user traffic profiles for resource provisioning (bandwidth allocation) in residential networking and derived a flow-based application classifier. Furthermore, the residential user traffic profiling investigated in chapter 3 and chapter 4 and further utilized in an experimental residential SDN framework in the present chapter relied on using IP address mappings of popular applications to classify user traffic flows. The approach presented a scalable and computationally effective solution to traffic classification, leading to the derivation and analysis of user traffic profiles. Traffic identification using IP address and port mappings is well-suited for environments where a more accurate data source addressing scheme is available to network administrators (e.g., enterprise servers, data centers), to accurately map user flows to service usage. For residential networks, however, and enterprise environments where users are frequenting a range of Internet services, traffic classification using IP address and port numbers is far from an ideal solution. As examined during chapter 4, the IP and port addressing

used for traffic identification scheme fell short of classifying P2P and gaming traffic. The respective unknown traffic flows had to be manually examined by reverse DNS lookups on destination IP addresses and port mappings to estimate representative application usage.

Part 2 of this thesis therefore, starts by investigating and designing an automated flow based traffic classification approach employing two popular machine learning techniques used in tandem. The proposed per-flow classification method aims to yield highly accurate classification results and can be used for Internet application identification in real-time, for user traffic profiling in residential as well as enterprise environments. Additionally, part 2 also investigates and analyses the benefits of using profiling based SDN traffic management in enterprise environments, offering operators increased level of granularity in provisioning network resources through the centralized SDN control plane.

PART II – Enterprise Traffic Management

Chapter 6 Classification of Internet Traffic Flows

6.1 Introduction

Traffic classification methods using flow and packet based measurements have been previously researched using various techniques ranging from automated machine learning (ML) algorithms to deep packet inspection (DPI) for accurate application identification. Port and protocol analysis, once the default method for traffic identification, is now considered obsolete as most applications use dynamic ports, employ HTTPS or encrypted SRTP, or use tunnelling, which makes classification close to impossible. Deep packet inspection (DPI) is useful, however, the computational overhead and additional hardware required for packet analysis severely limits its practical implementation for network operators [211]. Moreover, aggregation based traffic monitoring techniques using flow measurements have proliferated in recent years due to their inherent scalability and ease of implementation as well as compatibility with existing hardware using standardized export formats such as NetFlow and IPFIX [12]. However, despite an increase in use, flow based network monitoring also encountered traffic classification challenges mainly due to frequent obfuscation and encryption techniques employed by many applications [213-215]. Most automated machine learning classification algorithms utilizing NetFlow involve significant processing overhead and sometimes employ sanitized input requiring simultaneous computations on flow records and packet traces to obtain meaningful results [213][216-217]. Additionally, popular Internet applications generate convoluted sets of flows representing content specific and auxiliary control flows, making application identification on a per-flow basis even more challenging. Accurate traffic classification of user traffic flows however, is fundamental to user profiling and achieving greater precision in understanding user trends for subsequent integration in an SDN based traffic engineering framework.

The present chapter, therefore, proposes a per-flow C5.0 decision tree classifier by employing a two-phased machine learning approach while solely utilizing the existing quantitative attributes of NetFlow records. Flow records for fifteen popular internet applications were first collected and unique flow classes were derived per application using k-means clustering. Based on these pre-classified flows (the ground truth data), the C.50 classifier is subsequently trained for highly granular per-flow application traffic classification. The classified applications include YouTube, Netflix, Daily Motion, Skype, Google Talk, Facebook video chat, VUZE and Bit Torrent clients,

Dropbox, Google Drive and OneDrive cloud storage, two interactive online games, and the Thunderbird and Outlook email clients.

The remainder of this chapter is organized as follows. Section 6.2 presents related background work in traffic classification and gives an overview of k-means clustering along with C.50 algorithm with respect to flow based application classification. Section 6.3 elaborates on data collection, pre-processing and feature selection methodology. Section 6.4 details flow clustering using k-means and discusses the derived flow classes. Section 6.5 evaluates the accuracy of the resulting C5.0 classifier while section 6.6 compares the performance and computation overhead of the proposed approach with state of the art ML based classification schemes. Final conclusions are presented in section 6.7.

6.2 Background

The following subsections present a comprehensive overview of state of the art in traffic classification as well as consider related work in addressing flow level classification challenges using supervised, unsupervised and cascaded ML techniques. A brief outline of k-means clustering and C5.0 machine learning techniques in the context of traffic classification is detailed afterwards.

6.2.1 Traffic classification methodologies and related work

Traffic classification serves as a fundamental requirement for network operators to differentiate and prioritize traffic for a number of purposes, from guaranteeing quality of service to anomaly detection and profiling user resource requirements. Consequentially a large body of research focused on traffic classification, such as [218-223], along with comprehensive surveys [224-226], which reflect the interest of the networking community in this particular area. From a high-level methodology perspective, traffic classification research can be broadly divided into port and packet payload based classification, behavioural identification techniques and statistical measurement based approaches [226]. A summary of the prevalent classification approaches, their traffic feature usage and associated algorithms is given in Table 6.1. While port-based classification techniques are now considered obsolete given the frequent obfuscation techniques and dynamic range of ports used by applications, packet payload inspection methods remain relevant primarily due to their high classification accuracy. Payload based classifiers inspect packet payloads using deep packet

inspection (DPI) to identify application signatures or utilize a stochastic inspection (SPI) of packets to look for statistical parameters in packet payloads. Although the resulting classification is highly accurate, it also presents significant computational costs [226-228] as well as being error-prone in dealing with encrypted packets. In comparison, behavioural classification techniques work higher up the networking stack and peruse the total traffic patterns of the end-points (hosts and servers) such as the number of machines contacted, the protocol used and the time-frame of bi-directional communication to identify the application being used on the host [229-232]. Behavioural techniques are highly promising and provide a great deal of classification accuracy with reduced overhead compared to payload inspection methods [218][223]. However, behavioural techniques focus on end-point activity and require parameters from a number of flows to be collected and analysed before successful application identification. With increasing ubiquity of flow-level network monitoring which presents a low-cost traffic accounting solution, specifically utilizing NetFlow due to scalability and ease of use, statistical classification techniques utilizing flow measurements have gained momentum [212][218-222][233]. Statistical approaches exploit application diversity and inherent traffic footprints (flow parameters) to characterize traffic and subsequently derive classification benchmarks through data mining techniques to identify individual applications [234]. Statistical classification is considered lightweight and highly scalable from an operational point of view, especially when real-time or near real-time traffic identification is required. While traffic classification in the network core is increasingly challenging and seldom implemented, application flow identification at the edge or network ingress, as detailed in [226], allows operators to shape the respective traffic further upstream. Statistical flow based traffic classification however, due to minimal number of available features in a typical flow record such as NetFlow, leads to low classification accuracy and increasingly rely on additional packet payload information to produce effective results [218-222]. The present work picks up from this narrative and solely utilizes NetFlow attributes using two-phased machine learning (ML), incorporating a combination of unsupervised k-means based cluster analysis and C5.0 based decision tree algorithm to achieve high accuracy in application traffic classification.

Typical statistical flow-level classification can be further sub-divided based on the type of ML algorithm being used i.e. supervised or unsupervised. Unsupervised methods alone do not rely on any training data for classification and, while being time and resource efficient, especially with large data sets, encompass significant limitations hampering their wider adoption. Firstly, cluster analysis is mostly done offline and relies on evaluating stored flow records in statistical applications for

Table 6.1. Traffic Classification Approaches

Category	Classification Methodology	Attribute(s) Used	Granularity	Processing time	Sample Tools/ ML Techniques
Port based	Protocol port	Protocol ports	High	Low	Any (custom), PRTG network monitor [174], Nagios [284], Wireshark[256]
Payload Inspection	Deep packet inspection	Payload inspection of e.g., first n packets, first packet per direction	High	High	OpenDPI [211], nDPI [253], L7 (TIE) [245]
	Stochastic packet inference	Statistical properties inherent in packet header and payload	High	High	Netzob [282], Polyglot [283], KISS[222]
Behavioural techniques	End-point behaviour monitoring	Identifying host (communication) behaviour pattern	Low	Moderate	BLINC [251], SVM [271], Naïve Bayes [267]
	Traffic accounting	Heuristic analysis of inspected packets, flows	High	High	ANTCs [281], Naïve Bayes [267], Bayesian Network [274]
Statistical approaches	Packet based	Packet and payload size, inter-packet arrival time	High	Moderate	kNN [266], Hidden Markov/ Gaussian Mixture Models
	Flow based	Duration, transmission rate, multiple flow features	Low	Low	k-Means/ Hierarchical clustering [237], J48 [240], C5.0 [241], BFTree [269], SVM [271]

cluster learning and traffic identification [235][236]. Secondly, unsupervised clustering quite often also requires additional information from packet level traces requiring specialized hardware and is therefore considered an expensive option for network operators [237][238]. Lastly, once traffic records have been clustered, defining optimal value ranges of classification attributes for real-time systems is seldom easy and highly dependent on the dataset used [239].

Supervised ML algorithms, in contrast, require a comprehensive training dataset to serve as primary input for building the classifiers; the completeness of the dataset, together with the ability of the method to discriminate between classes, is the decisive factor for the accuracy of the method.

Although considered favourable in terms of presenting a discrete rule set or decision tree for identifying applications, supervised training also falls short of presenting a complete solution to classification challenges, as a highly accurate training/test data set (also referred to as ground-truth data) is required prior to further use. To aid in obtaining accurate ground-truth data, several ideas have been explored. Separate offline traffic identification systems were used to pre-process and generate training data for online classifiers in [240]. Custom scripts were employed in [241] on researcher machines to associate flow records and packets with application usage. Deep packet inspection was used to obtain application names for labelling training data in [242]. However, obtaining accurate ground-truth data considering only singular application class labels for subsequent training of the supervised ML classifier falls significantly short of recognizing the different flows generated per application [235-242]. Internet applications generate a convoluted set of flows, including both application initiated content-specific or auxiliary control flows as well as other functional traffic such as DNS or multicasts. Per-flow traffic classification hence requires a full appreciation of the peculiar traits and types of flows (classes) generated per application to eliminate the classification system relying on time window analysis or packet derivative information to achieve higher classification accuracy.

To increase the flow classification accuracy, cascaded classification methodologies employing a combination of algorithms as well as semi-supervised ML approaches have also been previously explored. Foremski et. al [243] combined several algorithms using a cascaded principle where the selection of the algorithm to be applied for each IP flow classification depends on pre-determined classifier selection criteria. Jin et. al [233] combined binary classifiers in a series to identify traffic flows while using a scoring system to assign each flow to a traffic class. Additionally, collective traffic statistics from multiple flows were used to achieve greater classification accuracy. Similarly, Carela-Espanol et. al [244] used k-dimensional trees to implement an online real-time classifier using only initial packets from flows and destination port numbers for classification. Donato et. al [245] introduced a comprehensive traffic identification engine (TIE) incorporating several modular classifier plug-ins, using the available input traffic features to select the classifier(s), merging the obtained results from each and giving the final classification output. A similar approach was followed in Netramark, [248] incorporating multiple classifiers to appraise the comparative accuracy of the algorithms as well as use a weighted voting framework to select a single best classification output. Another prominent ML tool used in traffic classification studies is Weka [249], incorporating a java-based library of supervised and unsupervised classifiers, which can be readily implemented on test data-set to evaluate the accuracy of the results from each methodology. Using

multiple classifiers and selecting the best choice for classifying each traffic flow through voting or even combining the results for a final verdict, however, does not specifically consider refining the ground-truth data to fully account for the multiple flow classes (per application) and their subsequent identification. Additionally, merging multiple instances of classifiers raises scalability issues with regards to their real-time implementation.

Semi-supervised learning techniques on the other hand, use a relatively small amount of labelled data with a large amount of unlabelled records to train a classifier [278]. Two ML algorithms, unsupervised and supervised, were combined in [279] and the scheme used a probabilistic assignment during unsupervised cluster analysis to associated clusters with traffic labels. Zhang et. al [280] proposed using a fractional amount of flows labelled through cluster analysis to train and construct a classification model specifically focusing on zero-day application identification. The sole use of cluster analysis to serve as a means for identifying applications and generating training data without either additional manual or automated validation may, however, lead to incorrect traffic labelling. Unmapped flow clusters from unsupervised learning were for example, attributed to unknown traffic in [279]. Error-prone labelling of flows through cluster analysis using semi-supervised approaches may therefore result in significant misclassification penalties.

Sub-flow qualification is paramount to fully apply network policies such as guaranteeing application QoS, profiling user activity and accurately detecting network anomalies. Furthermore, correct sub-flow identification aids in reducing the over-time degradation of supervised algorithms by accounting for the multiple types of flow classes and their respective parameters per application, reducing the unseen examples. The approach presented in this chapter refines the acquired ground-truth data by segregation of pre-labelled application flows through independent unsupervised clustering, thereafter used to train a supervised C5.0 decision tree. The resulting classifier is hence, able to recognize the multiple flow classes even from the same application without combining the results from multiple classifiers or using popular voting. This also increases the scalability of the final decision tree which can be implemented as a stand-alone system at suitable traffic aggregation points in the network capable of real-time traffic classification.

Finally, as noted in [246], [247], and [235], given the variety of classification methodologies, dissimilar traffic traces as well as the diversity in flow classification features, benchmarking the performance of classification algorithms is a difficult undertaking. In the present work, the widely used classification tool Weka [249] was employed to yield a qualitative comparison in terms of the

accuracy and computational overhead of the proposed design against some state of the art classification methods.

6.2.2 K-Means clustering

Flow-level clustering requires partitioning the collected flows per application into groups based on exported NetFlow attributes. Based on the computational efficiency documented in several recent traffic classification studies the present scheme uses the prominent unsupervised k-means clustering for unsupervised segregation of traffic flows from each examined application. The k-means clustering algorithm is preferred over other methods such as hierarchical clustering due to its enhanced computational efficiency [219][242]. As observed during the profiling evaluation study carried out in chapter 4, k-means led to producing tighter and more meaningful profile clusters compared to other techniques. In the present context, using k-means clustering Eq. 3.1., c_j represents cluster centre, *n* equals the size of the sample space (collected flows) and *k* is the chosen value for number of unique clusters (flow classes). Hence, using k-means, *n* flows can be partitioned into *k* classes. To calculate the optimal number of clusters, the previously tested Everitt and Hothorn graphical approach [188],is utilized.

6.2.3 C5.0 machine learning algorithm

The C5.0 algorithm and its predecessor C4.5 described in [240], attempt to predict a dependent attribute by finding optimal value ranges of an independent set of attributes. At each stage of iteration, the algorithm aims to minimize information entropy by finding a single attribute that best separates different classes from each other. The process continues until the whole sample space is split into a decision tree isolating each class. Hence, in a sample space comprising *n* application flow classes, if training data is given by pre-classified samples given by vector S, Eq. 6.1. Each sample flow f_n may consists of a j-dimensional vector, Eq. 6.2, where, z_j represents independent attributes which are used to identify the class in which f_n falls.

$$S = [f_1, f_2, f_3, f_n] \quad (6.1)$$

$$f_n = [z_1, z_2, z_3, z_j] \quad (6.2)$$

C5.0 could therefore, be used to build a decision tree utilizing flow attributes z_j of each sample f_n from pre-classified training data. C5.0 also includes advanced options for boosting, pruning and winnowing to enhance accuracy and computational efficiency of the resulting decision-tree

classifier [241]. The adaptive boosting proposed in [32] generates a batch of classifiers instead of a single classifier and uses vote count from each classifier on every examined sample to predict the final class. Advanced pruning options remove parts of the classification tree representing relatively high error rate at every stage of iteration and once finally for the complete tree to reduce performance caveats. Finally enabling winnowing reduces the feature-set required for classification by removing covariates with low predictive ability during classifier training and cross validation stage.

6.3 Methodology

To address the challenges of obtaining high quality ground truth data incorporating flow class segregation and identification in each of the examined applications, the proposed classification technique utilizes unsupervised cluster analysis and supervised classifier training in tandem. A high level overview of the traffic classification scheme is shown in Fig. 6.1 with a description of principal steps as follows.

- *Pre-processing:* Internet traffic is collected from end-user machines and marked with application labels accordingly (e.g. Skype, YouTube, etc.) using a localized operational packet level classifier. Application labelled traffic is afterwards exported as flows using a flow exporting utility for unsupervised cluster analysis.

- *Cluster analysis:* Using unsupervised k-means, flows belonging to individual applications are separately cluster analysed to extract unique sub-classes per application, offering a finer granularity of the classification (e.g. YouTube and Netflix flows would be classed as Streaming and Browsing).

- *Classifier training:* Flows marked with their k-means clusters, indicating the sub-class they belong to, are afterwards fed to a C5.0 classifier for supervised training, leading to a decision tree.

- *Evaluation:* A separate data set is used for testing the accuracy of the algorithm. For each NetFlow record the trained C5.0 classifies the application and the sub-class of the flow based on their respective attributes, ingrained during decision tree creation.

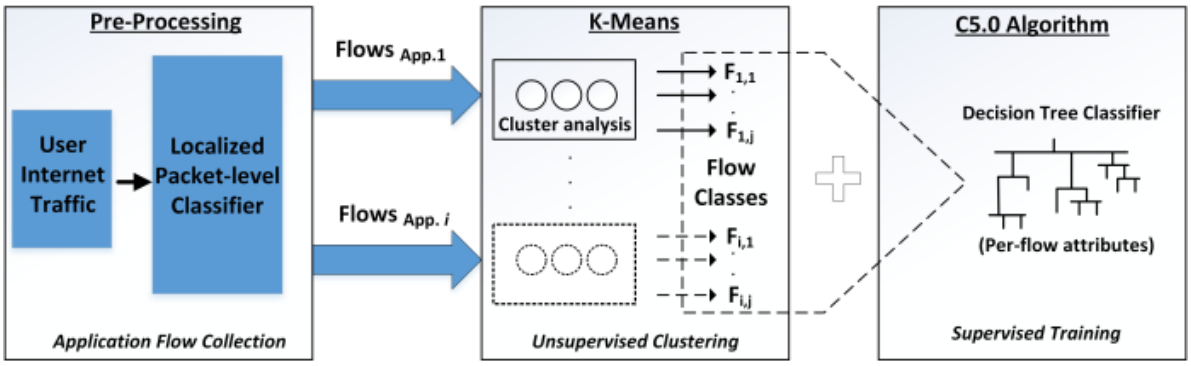


Figure 6.1. Traffic classification scheme

The following subsections detail the methodology used for collecting NetFlow records from user machines, flow customization, k-means clustering and designing feature-sets for the C5.0 classifier.

6.3.1 Data collection

To increase the scalability of the resultant classifier in identifying traffic from different network settings, NetFlow records were collected from two environments (i) a typical residential premises using broadband connection and (ii) an academic setting using corporate Internet as depicted in Fig 6.2. In order to accurately isolate traffic for each of the fifteen examined applications, a localized extension of packet-level classifier nDPI [253] was used on the researcher's machines excluding references to application data or the end-point identity of users for anonymity similar to [250] and [251]. The nDPI is based on the *libcap* and OpenDPI library [46] and is continuously updated to increase the number of applications and protocols that can be successfully identified. Once the traffic from the examined applications was identified and marked with application names, it was converted to the NetFlow format using the *softflowd* utility [252]. A total of approximately 13.6 million flows were collected and marked with application labels. Table 6.2 presents a summary of collected flows including the bytes, flows, timeframe of the traffic collection and the duration associated with each application. The NetFlow records were afterwards subjected to further pre-processing i.e. feature-set expansion using the nfdump utility [255] and creation of bi-directional flows before being exported to individual application storage filers as detailed in the following section.

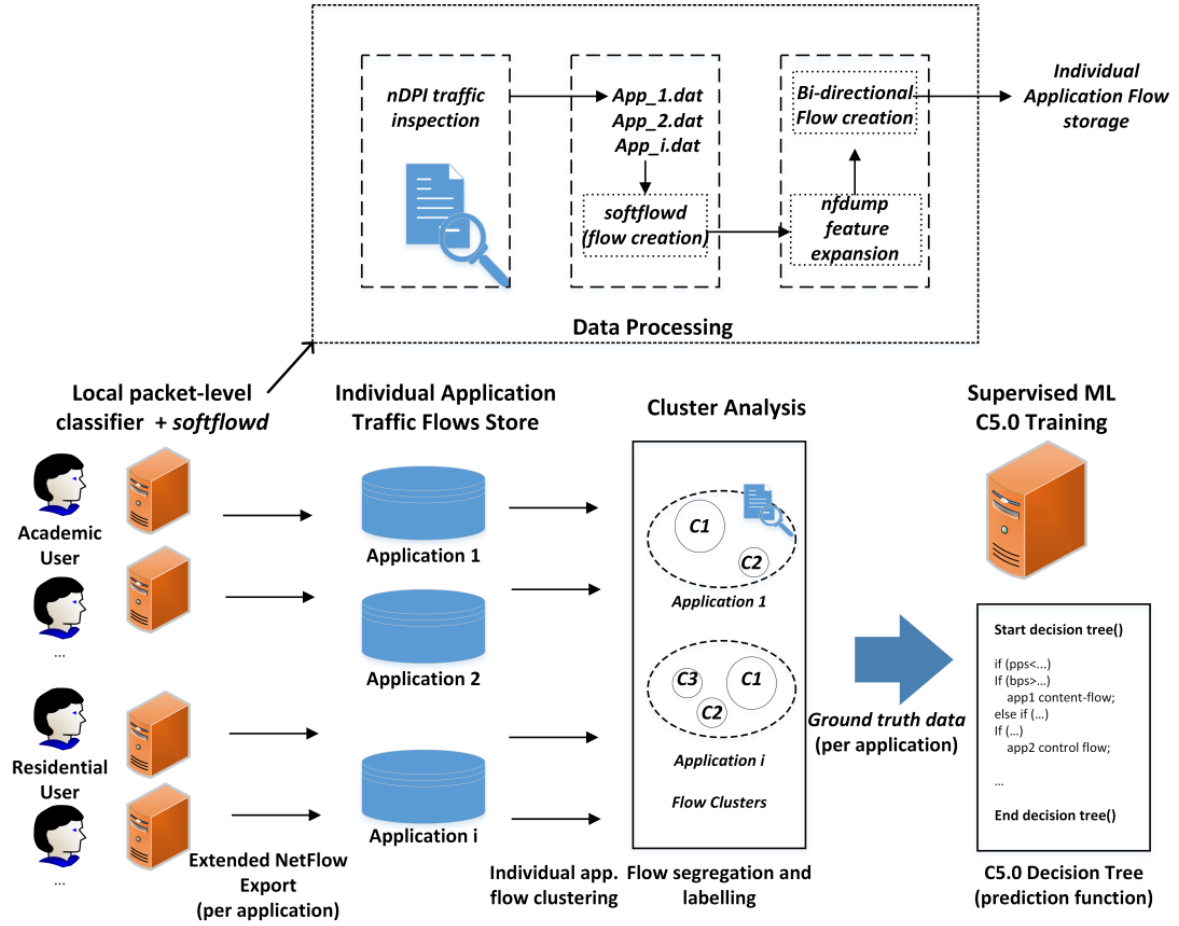


Figure 6.2. Data collection and pre-processing workflow

6.3.2 Customising NetFlow records

NetFlow by default outputs 5-tuple address, port and protocol connection information <SrcIP, DstIP, SrcPo, DstPo., Proto.> along with the timing and interface relating to each flow. Transmitted and received flows are, however, not correlated by default. Generally considered as lacking an extensive set of attributes, it further extrapolates the use of packet traces for traffic identification as highlighted in [239-239]. To fully explore the prediction ability of NetFlow attributes with the proposed methodology, *nfdump* [255] was used to expand the NetFlow output to display flow duration, number of packets, data rate (bits per second), packet transfer rate (pps) and output bytes per packet (Bpp) for each flow, then transmitted and received flows were correlated to output a 17 tuple bi-directional flow as shown by the snippet in Fig. 6.3.

Table 6.2. Traffic Collection Summary

Traffic Class	Application	Bytes (x10^6)	Flows	Dates	Duration (hrs)
Video streaming	YouTube	16093.87	879641	[09-12]/09/2015	6.89
	Netflix	11586.61	454985	[08-09]/09/2015	5.65
	DailyMotion	11258.12	398412	[15-16]/03/2016	5.31
Video Chat/ VoIP	Skype	6251.06	1492380	[08-17]/10/2015	9.45
	Gtalk	4584.02	1025260	[14-18]/03/2016	4.25
	Facebook Messenger	7824.13	1158302	[15-21]/03/2016	3.28
P2P Torrent	VUZE Torrent	131611.31	1318749	[20-23]/09/2015	4.28
	Bit Torrent	154138.97	1308881	[20-23]/09/2015	3.56
Cloud Storage	Drop Box	211833.57	408677	[11-23]/09/2015	1.56
	Google Drive	158923.52	358426	[20-23]/03/2016	2.31
	OneDrive	186358.21	325854	[21-27]/03/2016	1.81
Online Games	8ball Pool	953.91	1358425	[10-13]/10/2015	0.35
	Treasure Hunt	1158.28	1592362	[15-22]/03/2016	2.11
Email Client	Thunderbird	1401.36	821484	[15-31]/08/2015	2.21
	Outlook	1854.54	698722	[19-31]/03/2016	3.55

	SrcIP	DstIP	Prot.	SrcPo	DstPo	Tx.B.	Tx.Pkt.	Tx.s.	Tx.bps.	Tx.pps.	Tx.Bpp.	Rx.B.	Rx.Pkt.	Rx.s.	Rx.bps.	Rx.pps.	Rx.Bpp.
12	*Private IP* Address	*Website/Application*	TCP	59648	80	1737	10	16.551	839	0	173	2768	10	16.542	1338.0	0	276
13	*Private IP* Address	*Website/Application*	TCP	50254	443	763	8	0.073	83616	109	95	4571	7	0.063	580444.0	111	653
14	*Private IP* Address	*Website/Application*	TCP	37832	443	397	5	0.078	40717	64	79	3657	4	0.041	713560.0	97	914
15	*Private IP* Address	*Website/Application*	TCP	47216	443	2663	12	1.291	16501	9	221	5718	11	1.279	35765.0	8	519
16	*Private IP* Address	*Website/Application*	TCP	53509	443	883	10	0.278	25410	35	88	4472	9	0.243	147226.0	37	496

Figure 6.3. 17-tuple bi-directional NetFlow records

6.3.3 Extracting flow classes (k-means clustering)

Popular applications such as YouTube or Skype generate an intricate set of flows between various web servers and the client depending on their underlying content distribution, load balancing and authentication schemes [256-259]. While DPI based traffic classification is useful in identifying the respective applications, it does not specifically segregate different flows generated per application attributed to the primary application content or control signalling, session establishment, embedded webpage advertisements, etc. Per-flow classification consequently

requires a separation of content specific and supplementary flows to retrieve the different flow classes generated per application for subsequently training and testing the classifier. Flow classification is not possible using supervised ML alone due to lack of information about the flow classes generated by an application, requiring an independent technique for per-application flow segregation. The K-means algorithm was therefore, independently applied on paired bi-directional flows generated per application in order to retrieve the respective flow classes. Due to extensive repetition of source and destination IP addresses, port numbers and protocol information in the collected data, these were deemed scalar entities for analysis and excluded while clustering. The remaining attributes chosen to isolate application specific flows from auxiliary data per application for further analysis comprise the following:

(i) **Transmitted/Received bytes** Tx.(B)|| Rx.(B): The traffic volume (bytes) that is transmitted/received per flow.

(ii) **Transmitted/Received packets** Tx.(pkt)||Rx.(pkt): The number of packets per flow.

(iii) **Transmitted/Received flow duration** Tx.s|| Rx.s: The total flow duration.

The clustering vector per application could therefore, be represented by the following Eq. 6.3.

$$F_{ij} = [Tx.B_{ij}, Tx.pkt_{ij}, Tx.s_{ij}, Rx.B_{ij}, Rx.pkt_{ij}, Rx.s_{ij}] \quad (6.3)$$

In Eq. 6.3 above, *i* and *j* are unique per application and per flow respectively. Additionally, using the per-flow measurements given in Eq. 6.3, the data rate (bits and packets per second) and packet size (bytes per packet) can be output from the *nfdump* utility. The bidirectional flows represented by vector F_{ij} once split into *k* clusters represent the types of flows per application. Once segregated, the flows per application were subsequently labelled with the respective flow class before datasets for all the fifteen examined applications were combined and split in equal proportions (~50%) for training and testing the C5.0 ML classifier.

6.3.4 Feature selection

Feature set selection is of paramount importance for training the classifier, given that these should be predictive and must correctly classify the application traffic. The selected features must also closely link to the flow classes derived from k-means clustering and utilize their NetFlow values to discriminate between different application flows. NetFlow attributes can be broadly grouped by transport layer parameters and network layer traffic statistics for each flow. Both groups were

studied for classifier training individually and in combination to examine their efficiency for classification. Additionally, minimizing the set of features for traffic classification also minimizes the processing overhead involved in creating decision trees and reduced classification time. Four sets of features sets were, therefore, devised around transport and network layer features translating for the independent attributes $z_{j,}$ given in Eq. 6.2 as shown in Table 6.3. Set 1 included source and destination port numbers along with protocol information. Set 2 used source and destination ports but, rather than using actual port numbers these were labelled as Known (0-1023) and Registered/Unknown (>1023) aiming to evaluate classification accuracy on basic port information alone. Set 3 included 12 flow attributes excluding source and destination IP addresses, port and protocol information while Set 4 represented the same as ratios thereby, reducing the feature set to 6 covariates with the intention of compressing the size of resulting decision tree even further.

6.4 Unsupervised flow clustering

6.4.1 Calculating flow classes per application – value of k

A total of 6.8 million bi-directional flows were cluster analysed independently for each application using the computationally efficient Hartigan and Wong implementation of k-means in R [175]. Since the value of k influences directly the number of flow clusters (classes) per application, the Everitt and Hothorn method was employed to determine the k number per application [188]. This graphical technique plots *within cluster sum of square values (wss)* against the number of clusters k, with the curve in plot signifying an appropriate number of clusters that fit the input data. The plot of *wss vs. k* of flow records for each application is given in Fig 6.4 - 6.8 [Appendix – 3.1]. The maximum *within-cluster variance* between successive values was calculated according to Everitt and Hothorn criteria in reaching the optimal cluster number per application. The respective flow records were afterwards marked with the individual cluster colour. Table 6.4 details the optimal number of clusters translating for different types of flows classes determined per application along with the 'within sum of squares' per cluster to 'total sum of square distance' between clusters (wss / total_ss) representing the tightness of these clusters in covering the entire sample space i.e. flow records. A small sample set comprising approximately 1K bi-directional flows from each cluster was afterwards analysed offline to assign the respective flow labels as detailed in the following section.

Table 6.3. NetFlow Feature Sets for C5.0 Classifier Training

Set 1	**Set 2**
Protocol and Port information: • Source and Destination **Port <u>Num</u>** • Protocol **(TCP, UDP)**	Protocol and Port information: • Source and Destination **Port <u>Labels</u>** • Protocol **(TCP, UDP)**
Set 3	**Set 4**
Flow Parameters: • Received and Transmitted Packets **(Rx.Pkts, Tx.Pkts)** • Received and Transmitted Packet Rate **(Rx.pps, Tx.pps)** • Received and Transmitted Data Rate **(Rx.bps, Tx.bps)** • Received and Transmitted Bytes per Packet	Flow Parameter Ratios: • Received Packets to Transmitted Packets **(Rx.Pkts/Tx.Pkts)** • Received to Transmitted Packet Rate **(Rx.pps/Tx.pps)** • Received to Transmitted Data Rate **(Rx.bps/Tx.bps)** • Received to Transmitted Bytes per Packet **(Rx.Bpp/Tx.Bpp)**

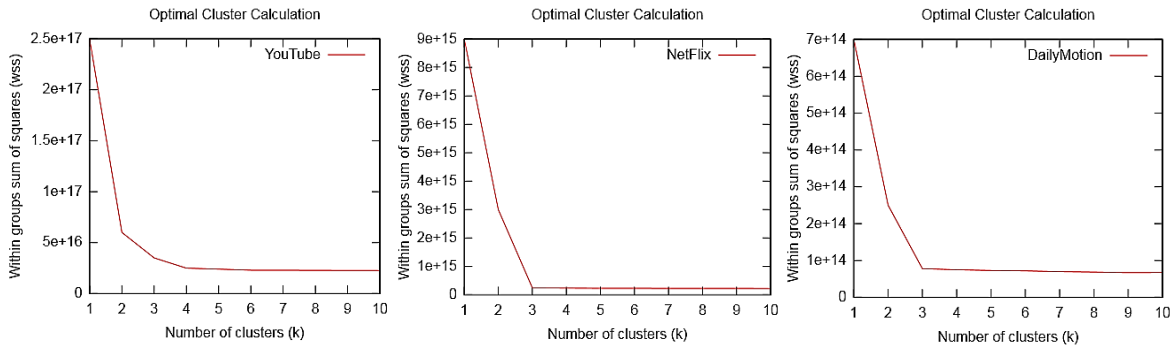


Figure 6.4. Inner-cluster variance vs. k – (a) YouTube, (b) NetFlix and (c) DailyMotion

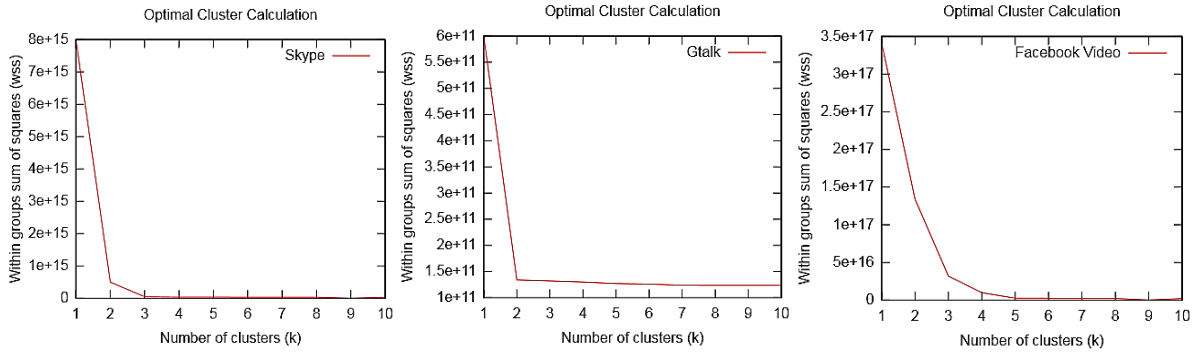


Figure 6.5. Inner-cluster variance vs. k – (a) Skype, (b) GTalk and (c) Facebook (Messenger)

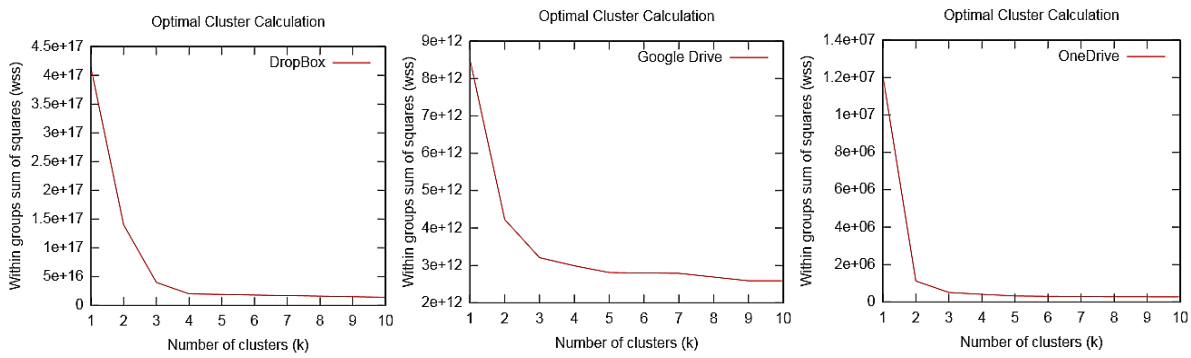


Figure 6.6. Inner-cluster variance vs. k – (a) DropBox, (b) GoogleDrive and (c) OneDrive

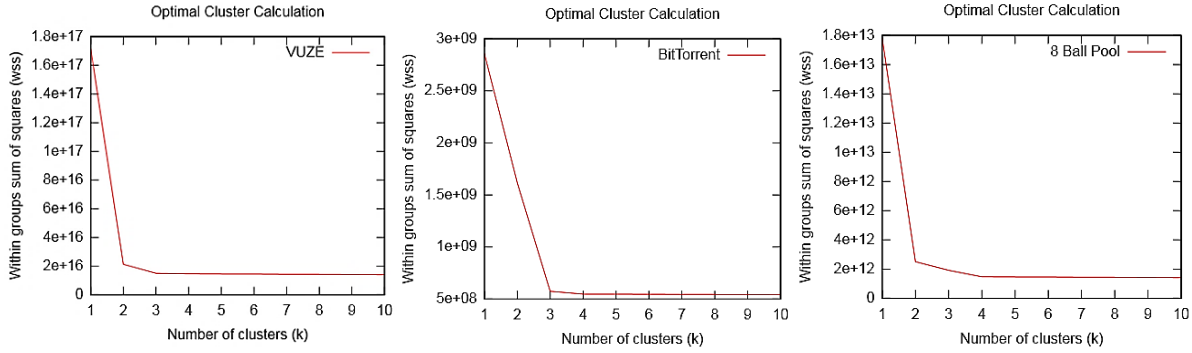


Figure 6.7. Inner-cluster variance vs. k – (a) VUZE, (b) BitTorrent and (c) 8-ball Pool

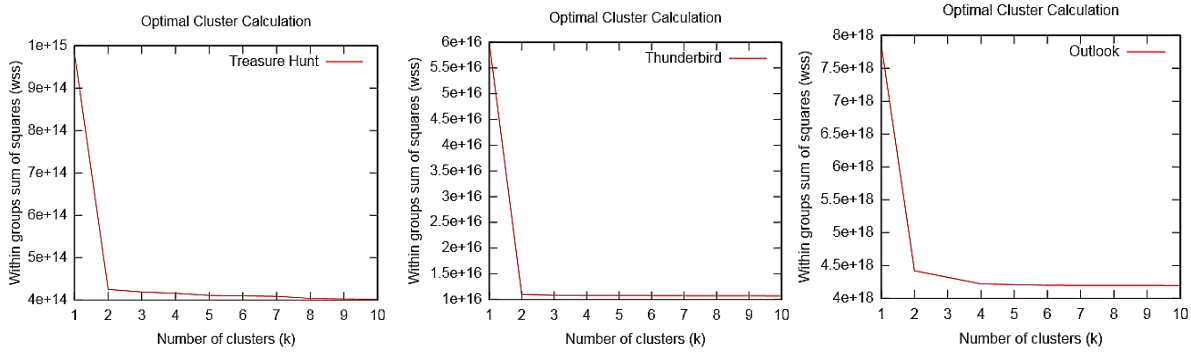


Figure 6.8. Inner-cluster variance vs. k – (a) TreasureHunt, (b) Thunderbird and (c) Outlook

6.4.2 Analysis

YouTube access seemed to be solely used for *streaming* (and not content upload) in the present case and the corresponding clusters indicated 3 unique flow classes generated as shown by the graph in Fig 6.4(a). According to YouTube traffic analysis studies carried out in [256][257], these were narrowed to three unique flow classes and attributed to content-streaming, website browsing (or video searches) and redirections between YouTube and other Google content distribution servers. Netflix and Daily Motion video streaming, similarly showed three flow classes, two for video content-streaming having different download rates corresponding to start of video succeeded

by steady buffering stage and a third for user searches. For these applications, video streaming flows were labelled as 'streaming' while website searches and server redirections as 'browsing'.

The Skype client was used for *video with voice communication* rather than file sharing or instant messaging. Subsequent clustering produced two highly discriminate clusters given by the knee-point of the graph in Fig 6.5(a). Skype stores user information in a decentralized manner with Skype clients acting has host nodes that initiate connections with super nodes for registering with a Skype login server and exchanging continuous keep-alive messages [258]. The resulting overlay peer to peer network employs both TCP and UDP connections both for communication between host and super nodes as well as between two hosts running the client application [259][260]. One flow cluster was hence, determined to be directly associated with control features servicing connections and authentication between host and super nodes, having a much lower data volume and receiving rate and a significant number of unidirectional flows compared to the second group. The second flow cluster comprised of video calls between Skype clients having substantially higher data rate

Table 6.4. Segregated Flows per Application

Traffic Class	Application	Cluster (k)	wss/ total_ss	Content	Auxiliary Flows
Streaming	YouTube	3	87.3%	Streamin	Browsing
	Netflix	3	94.6%	Streamin	Browsing
	DailyMotion	3	95.1%	Streamin	Browsing
Comms./VoIP	Skype	2	98.8%	Comms.	Comm. Ctrl
	Gtalk	2	97.21%	Comms.	Comm. Ctrl.
	Facebook	3	92.12%	Comms.	Comm. Ctrl.,
Torrents/P2P	VUZE	3	97.9%	Torrent	Torr.Ctrl.
	Bit Torr.	3	91.2%	Torrent	Torr.Ctrl.
Cloud Storage	DropBox	3	89.2%	Up/Dwnl	Browsing
	Google Drive	3	88.15%	Up/Dwnl	Browsing
	OneDrive	3	92.14%	Up/Dwnl	Browsing
Gaming	8ballPool	2	88.4%	Game ctrl	Game Setup
	TreasureHun	2	91.98%	Game ctrl	Game Setup
Email	Thunderbird	2	99.14%	Email	Dir. Lookups
	Outlook	2	97.45%	Email	Dir. Lookups

and total data volume. The respective flows were labelled as ‘Comms. control’ and ‘Comms.’ accordingly. The same number of clusters were observed for Gtalk attributed to voice communication and control signalling with the Google content server with the later having a lower traffic footprint with respect to flow transmission duration and the average bit rate of the flows compared to the former. For Facebook messenger, however, three optimal clusters were observed, one with a high bit rate and duration similar to the VoIP calls observed in Skype and Gtalk, one for connection establishment and lastly one for the background live newsfeed being continuously updated on the Facebook page. The clusters were, thus accordingly labelled under ‘Comms’, ‘Comms. Control’ and ‘Browsing’ classes.

For *online cloud storage*, usually requiring low user interactivity as highlighted in [261], Drop box, Google Drive and OneDrive were examined. The applications employed file transfers ranging in size from 25KB to 1.5 GB, frequently in batches of 1, 5 and 10 files. Cluster analysis on generated traffic featured around 3 optimal flow clusters as represented by Fig 6.6. The three distinct flow clusters, after analysis were labelled as one each for file ‘uploads’ and ‘downloads’ and a third for interaction with the hosting website tagged ‘browsing”.

To examine *torrent applications*, the original Bit Torrent and VUZE derivative client were used on researcher machines’ to search and download different combinations of files with sizes ranging from 25 MB to over 1 GB. Cluster analysing these torrent flows resulted in three distinct clusters representing actual file download labelled as ‘torrent’ and later two as ‘torrent control’ responsible for further seeding of downloaded files and communication with other peers.

For online interactive Macromedia Flash player based pool and treasure hunt game, two clearly distinct flow classes as depicted in Fig. 6.7(c) and Fig. 6.8(a), responsible for initial ‘game setup’ and continued interactive ‘game control’ constituted all flows.

Lastly the email clients Thunderbird and Outlook were used with three distinct email accounts, Yahoo, Gmail and a corporate account. Cluster analysis revealed two discrete types of flows shown in Fig 6.8 (b) and (c). One flow cluster comprised sending and receiving email messages which in this case could also be easily identified by looking at well-known destination port assignments for SMTP, POP and IMAP protocols. The second flow class represented ‘directory lookups’ by the client using HTTP and SSL having significantly lower total data volume per flow compared to email messages.

Segregated flows of all applications were labelled with flow classes and combined into a single data set. The next section details the splitting of training and testing data and evaluates the C5.0 ML classifier.

6.5 C5.0 Decision tree classifier

Approximately 6.8 million flows were labelled with appropriate flow classes as a result of k-means cluster analysis, in accordance with Table 6.3. In order to comprehensively test classifier accuracy, the data set was further split in almost equal percentages (~50%) per flow class for training and testing purposes.

6.5.1 Classifier evaluation

C5.0 ML was applied on the training data set using feature sets 1 to 4, with alternate pruning and boosting options [Appendix – 3.2, 3.3]. As mentioned earlier, enabling pruning removes parts of the decision tree representing relatively higher error rates than others while adaptive boosting generates a batch of classifiers and uses voting on every examined sample to predict the final class. Classifiers were derived by enabling both options to analyse improvements in accuracy using the feature sets in Table 6.3. The resulting prediction accuracy for each attribute set is reported in Table 6.5. Set 1 included source and destination port numbers along with protocol information and resulted in in a maximum accuracy of 41.97% with the maximum allowed boosting factor of 100 and could easily be ruled out for use as standalone feature-set for classification. Set 2 used port name labelling instead of actual numbers and protocol information, resulting in considerably low accuracy even when compared to set 1 with uniformity in values regardless of boosting at 24.29%. Set 3 included twelve flow attributes and resulted in a significantly improved accuracy of 84.97% with a 10 boost. Finally, set 4 incorporating only flow ratio parameters led to a maximum accuracy of 75.03% with 100 times boost. In this particular instance disabling pruning resulted in a more accurate classifier at 75.70%. When used in combinations sets 2 and 4 presented lowest accuracy peaking at 77.42% while sets 1 and 4 as well as 2 and 3 resulted in reasonable level of classifier accuracy at 86.79% and 86.91% respectively. Set 1 and 3 combined showed a considerable improvement with classification accuracy peaking at 96.67% with a 100 boost while even with a 10 boost or a single classifier (no boost) the prediction results were 94.52% and 92.37% respectively.

The misclassification table, generated during training stage for this best combination (set 1 and 3) classifier is presented in Table 6.6 The highest number of discrepancies was observed between 'game setup' and 'torrent control' classes (229 flows). Estimated low in predictive ability, only one attribute, received packets per second (Rx.pps) was winnowed during training stage. The remaining 14 attributes used to build the resulting classifier along with their percentage use are given in Table 6.7.

Table 6.5. Feature Sets vs. Classifier Accuracy

Feature Set	Pruning = FALSE			Pruning = TRUE		
	No Boost	***Boost 10***	***Boost 100***	***No Boost***	***Boost 10***	***Boost 100***
Set 1	39.58	40.01	41.34	39.44	40.48	41.97
Set 2	24.29	24.29	24.29	24.29	24.29	24.29
Set 3	82.29	83.24	84.29	82.20	84.97	83.95
Set 4	73.18	75.51	75.70	73.18	72.62	75.03
Set 1 + 3	91.37	94.39	95.98	92.37	94.52	96.67
Set 1 + 4	84.48	87.47	86.47	84.48	86.42	86.79
Set 2 + 3	84.90	86.91	85.71	84.90	85.00	85.61
Set 2 + 4	74.37	77.07	77.21	74.37	76.83	77.42

Table 6.6. Misclassification Table for Best Feature-Set Combination (Training Stage)

Application Classified:	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
(a) Game_set.	156432										229	
(b) Game_ctrl		257707										
(c) Browsing	32		932493									
(d) Stor_dnld				63212								
(e) Stor_upld					56613							
(f) Email_mssg						257707						
(g) Email_dir							122343					
(h) Comms								257552				
(i) Comms_ctrl								87	561432		157	
(j) Streaming				35						77343		
(k) Tor_ctrl											203764	
(l) Torrent	89											453142

Table 6.7. Flow Attribute Usage

Flow Attribute Usage in Selected C5.0 Classifier		
Category	***Attribute***	***Percentage Use***
Protocol and Port	Protocol	80.62%
	Destination Port	100%
	Source Port	100%
Transmitted Flow (Tx) Attributes	Bytes [Tx.B]	100%
	Packets [Tx.Pkt]	100%
	Bits per second [Tx.bps]	100%
	Packets per sec [Tx.pps]	96.25%
	Bytes per package [Tx.Bpp]	100%
	Duration [Tx.s]	95.48%
Received Flow (Rx) Attributes	Bytes [Rx.B]	100%
	Packets [Rx.Pkt]	100%
	Bits per sec [Rx.bps]	100%
	Bytes per package [Rx.Bpp]	100%
	Duration [Rx.s]	98.61%

6.5.2 Confusion matrix analysis

The confusion matrix for selected classifier specifying cross-tabulation of predicted classes and observed values with associated statistics between different flow classes is given in Table 6.8. The highest errors occurred between ‘game control’ and ‘browsing’ flows (60114 or 1.76% of total tested flows), while no misclassification errors were observed between ‘game setup’ and ‘torrent control’ flows as witnessed during training cross-validation stage. The overall accuracy statistics are presented in Table 6.9. The value for the kappa co-efficient [262][263], which takes into account occurrences of accurately classified flows and is generally considered a more robust measure than simple percent agreement calculation, was also significantly high at 95.31%. The overall accuracy rate was also computed along with a 95 percent confidence interval (CI) for this rate (0.9364, 0.956) and a one-sided test to see if the accuracy is better than the ‘no information rate,’ which is taken to be the largest class percentage in the data (P-Value: Accuracy > NIR : < 2.2e-16) [264]. McNemar's test p-value however, was not available due to sparse tables (bi-directional flow vectors having very low or zero attribute values for some flow classes i.e. Skype control, etc.).

Table 6.8. Confusion Matrix Calculation for Optimal Classifier (Evaluation Stage)

Application Classified:	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
(a) Game_setup	156435											
(b) Game_ctrl		257718	60114									
(c) Browsing	632	25481	932494		4006							
(d) Stor_dnld				63208								
(e) Stor_upld					56611							
(f) Email_mssg						257710						
(g) Email_dir		3981	2561				122346					
(h) Comms								257552				
(i) Comms_ctrl			4587						561433			
(j) Streaming				1335						77341		
(k) Torrent										2078	453143	
(l) Tor_ctrl		5843	6154									203766

Table 6.9. Overall Statistics

Statistical Property	Value
Classifier Accuracy	96.67%
95% Confidence Interval (CI)	(0.9364, 0956)
No Information Rate	0.3332
P-Value (Acc > NIR)	< 2.2e-16
Kappa	0.9531
McNemar's Test P-value	NA

6.5.3 Sensitivity and specificity factor

For a given flow, the classifier's ability to accurately predict the flow class is characterized by the classifier sensitivity factor and to differentiate this flow from other flow classes, by its specificity factor. Both parameters are of significant importance an ascertaining a classifier's suitability for both flow identification and discrimination. The sensitivity and specificity bar graph for each flow class for the selected classifier are given in Fig. 6.9. Lowest sensitivity was recorded for cloud storage flows (87.67-89.89%) among all classes, also evident from Fig. 6.9 due to a higher mismatch between storage download and streaming (1335 or 0.039%) as well as storage upload and browsing flows (4006 or 0.11% of total tested flows). The corresponding specificity values for both storage

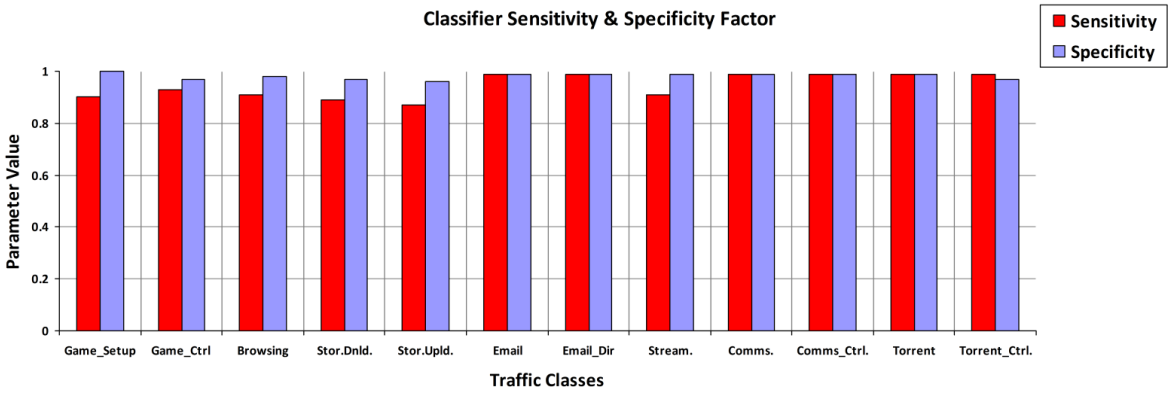


Figure 6.9. Classifier Sensitivity and Specificity Factor per Traffic Class

flow classes, however, being significantly high indicated correct differentiation ability of the classifier for this application and lower sensitivity factor accredited to other application flows being misclassified under this class. Communication and bit torrent traffic classes showed high sensitivity and specificity values. The selected classifier also showed high accuracy in detecting and differentiating between Email messages and directory lookups. The classification accuracy reported per flow class was also greater than 90% for all applications apart from Drop box which showed 87.67% accuracy due to mismatch with streaming and browsing flows. The specificity values, however, were substantively high without exception across all flow classes ranging between 98.37–99.57%. The results represent a highly granular classifier with ability to accurately identify application traffic as well as discriminate between flows generated by same application without employing any complex time window flow and packet analysis. As an added advantage, the approach only used a minor change in output formatting of NetFlow attributes together with basic scripting for creating bi-directional flows. The next section considers some alternate approaches for machine learning based traffic classification and compares their accuracy and computational overhead with the derived classifier.

6.6 Qualitative comparison

To undertake a comprehensive qualitative evaluation of the two-phased ML approach, alternate ML classifiers were appraised for their viability of use in per-flow traffic classification in relation to the proposed technique. Weka machine learning software suite (version 3.6.13), was employed to evaluate the eight most commonly utilized supervised machine learning algorithms in comparison with the proposed two-phased approach. The comparison evaluated (i) the classification accuracy of each algorithm, (ii) the computational overhead including the training and testing times to validate the results from each classification technique, and (iii) provide

perspectives on the scalability of the two-phased machine learning classifier. The classifiers used the same ratio of training and testing data set pools (marked with respective application class), where 50% of the flows were used for training the respective classifier and the remaining 50% flows were used for testing purposes. The machine learning algorithms evaluated are briefly described as follows.

J48/C4.5 decision tree, constructs a tree structure, in which each node represents feature tests, each branch represents a result (output) of the test, and each leaf node represents a class label i.e. application flow label in the present work [240][265]. In order to use a decision tree for classification, a given tuple (which requires class prediction) corresponding to flow features, walks through the decision tree from the root to a leaf. The label of the leaf node is the classification result. The algorithm was enabled with default parameters (confidence factor of 0.25 and reduced-error pruning by 3 fold) in the WEKA implementation of the present experiment to optimize the resulting decision tree.

K-nearest neighbours (KNN), computes the distance (Euclidean) from each test sample to the *k* nearest neighbours in the n-dimensional feature space. The classifier selects the majority label class from the *k* nearest neighbours and assigns it to the test sample [266]. For the present evaluation k=1 was utilized.

Naïve Bayes (NB), considered a baseline classifier in several traffic classification studies selects optimal (probabilistic) estimation of precision values based on analysis of training data using Bayes' theorem, assuming highly independent relationship between features [267][268].

Best-first decision tree (BFTree), uses binary splitting for nominal as well as numeric attributes and uses a top-down decision tree derivation approach such that the best split is added at each step [269]. In contrast to depth-first order in each iterative tree generation step [61][62], the algorithm expands nodes in best-first order instead of a fixed order. Both the gain and gini index are utilized in calculating the best node in tree growth phase. The algorithm was implemented with post-pruning enabled and with a default value of 5 folds in pruning to optimize the resulting classifier.

Regression tree representative (REPTree), is a fast implementation of decision tree learning which builds a decision/regression tree using information gain and variance with reduced-error pruning along with back fitting. Reptree uses regression tree logic to create multiple trees and selects the

best from all the generated trees. The algorithm only sorts values for numeric attributes once. It was implemented with pruning enabled with the default value of 3 folds.

Sequential minimal optimization (SMO), a support vector classifier trained using a sequential minimal optimization algorithm by breaking optimization problem into smaller chunks, solved analytically. The algorithm transforms nominal attributes into binaries and by default normalizes all attributes [271][272]. It was implemented using WEKA with normalization turned on along with the default parameters (the complexity parameter C=1, and polynomial exponent P=1).

Decision tables and naïve bayes (DTNB), is a hybrid classifier which combines decision tables along with naïve bayes and evaluates the benefit of dividing available features into disjoint sets to be used by each algorithm respectively [65]. Using a forward selection search, the selected attributes are modelled using NB and decision table (conditional probability table) and at each step, unnecessary attributes are removed from the final model. The combined model reportedly [273] performs better in comparison to individual naive Bayes and decision tables and was implemented with default parameters. The final classifier selected and used 5 attributes (out of 16 using backward elimination and forward selection search).

Bayesian network (BayesNet), an acyclic graph (directed) that represent a set of features as its vertices, and their probabilistic relationship as the graph edges [274]. While using the Bayes' rule for probabilistic inference, under invalid conditional independence assumption (in Naïve Bayes) BayesNet may outperform NB and yield better classification accuracy [275]. The default parameters i.e. SimpleEstimator was used for estimating the conditional probability tables of a BN in the WEKA implementation of BN on the training set.

The following sub-sections highlight a qualitative comparison between the above machine learning classification techniques and the proposed two-phased approach.

6.6.1 Comparative accuracy

The respective accuracy of each examined traffic class for multiple classifiers is given in Fig. 6.10. Overall, the two-phased approach surpassed or equated in per-flow classification with the alternate classification techniques. The algorithm achieved the highest accuracy for the game setup class of flows. For game control flows, alternate approaches such as kNN and REPTree provide a better

percentage of correctly identified flows. Comparatively lower accuracy reported for game control flows was considered earlier while evaluating the sensitivity of two-phased classifier, and was mainly due to misclassification errors (of game control) with the web-browsing flows. kNN and REPTree, however, provide a lower accuracy than two-phased ML for browsing and streaming flows. Similarly, for the streaming application tier, SMO based approach yielded highly accurate results when compared to the two-phased machine learning approach and minimal accuracy for the Email flows. For the communication application flows, almost all classifiers apart from NB (~63%) provided correct classification results (~80%). This was primarily due to the predictive ability of flow parameters for this set of applications. For torrent based flows, J48 decision tree along with BFTree provided almost 99.99% classification results, with BFTree (97.25%) exceeding the two-phased classifier which gave approximately 90.02% capability for flow identification of torrent control traffic due to mismatch with game control and browsing flows. In conclusion, different applications seem to be most accurately identified by different classifiers. In terms of overall accuracy, however, two-phased ML provided a much more coherent and applicable result at 96.67%, with the lowest accuracy attributed to SMO at approximately 53.2% correctly classified records.

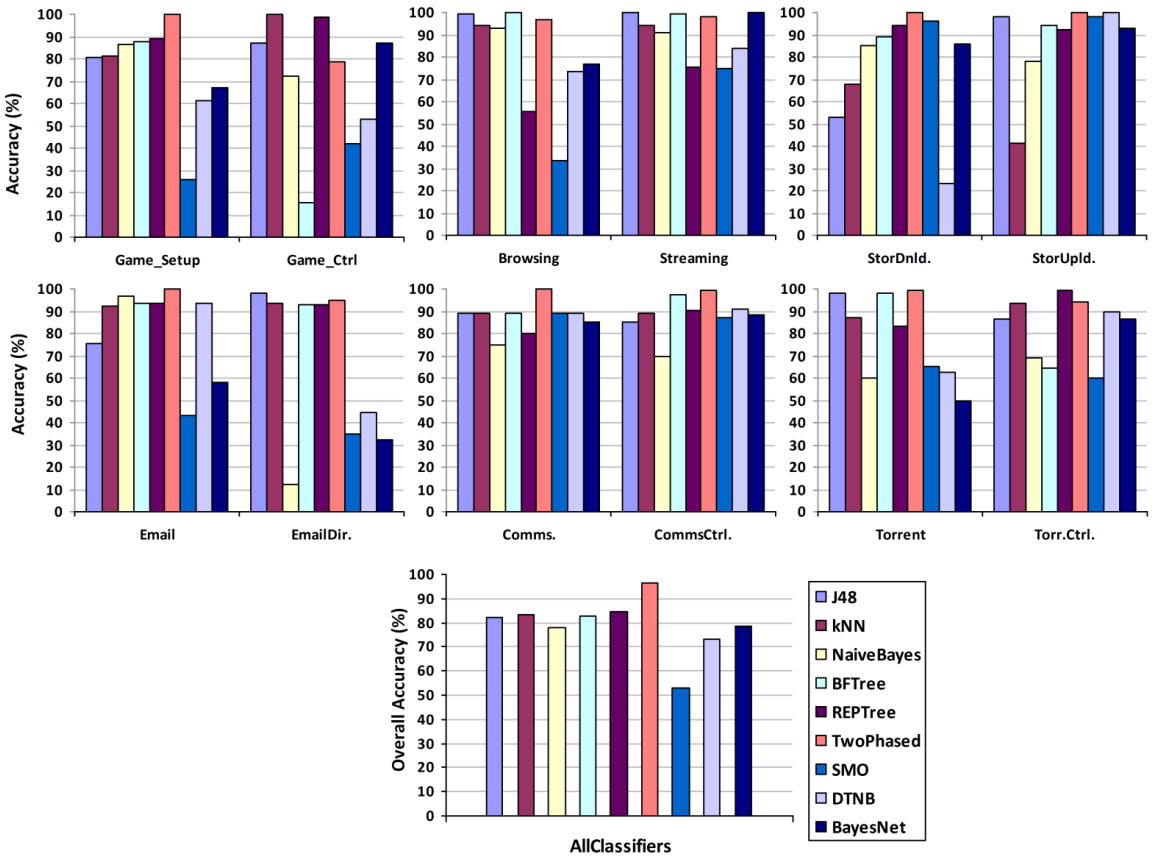


Figure 6.10. Comparative and average overall accuracy of machine learning algorithms for each traffic class

6.6.2 Computational performance

To evaluate the computational performance of the classifiers, each was independently implemented on a test machine (PC), an Intel based i54310-M processor chipset with two 2.70 GHz CPUs and 16GB of memory. The operating system used a GNU/Linux kernel (3.14.4 x64) and it was verified that no other user processes (apart from the WEKA software suite) were consuming CPU cycles or any of the operating system processes were CPU or I/O intensive. The two-phased ML evaluation included the combined cluster analysis and subsequent C5.0 training phase from labelled flows. This was done solely to examine the computational requirements of the unsupervised and supervised machine learning ensemble, excluding the ground-truth acquisition and refinement (i.e. DPI based application flow perusal and sub-class marking) which can be done offline and continuously on much greater data-sets in a practical network implementation. To give a realistic comparison, the alternate classifiers used the same application labelled flows (ground-truth). The average CPU utilization for each classifier in terms of the flow records and bytes processed (testing) are given in Fig. 6.11. A linear relationship was observed between the CPU utilization and the amount of records processed for all classifiers followed by a steady-state pattern albeit different consumption footprints. The kNN classifier had the highest CPU usage at up to 5.32% with a gradual decrease steadying at 4.21%. NB classifier had the lowest consumption at 1.61% while two-phased ML reported around 4.31% usage. Similarly the average memory usage per classifier in processing flow records and bytes of data are provided in Fig. 6.12. The BFTree algorithm had the highest memory usage at 190.28MB with the two-phased ML at 175.31MB. BayesNet had the lowest memory footprint with a steady-state value of approximately 50.14MB.

The average training and testing times with respect to three different sizes of flow sets (1000, 1 million and 3 million) for each classifier are depicted in Fig. 6.13. The training time for two-phased classifier was significantly high compared to other classifiers for flow-record size of 1000 flows. This was due to the in tandem processing of the two embedded algorithms used. The training-time relationship for most classifiers with respect to the size of training data at larger values of the latter was, however, non-linear. The training time for J48 for example, for both 1M and 3M flows was approximately the same averaging at around 59.35 minutes. Similarly, BFTree approximated at 60.12 minutes for 1M to 63.45 minutes for 3M flows respectively. The two-phased classifier also reported between 80.87 minutes to 84.51 minutes for the respective flow records in the training phase. This yields approximately on average 0.88 seconds spent training around 1K flows with a standard deviation (σ) of 1.137 between 1M and 3M flows. Hence, the proposed technique results in better performance in terms of training times in the steady-state with relatively larger data-sets.

However, as noted above it does not specifically consider the time duration involved in offline analysis of optimal cluster labelling following examination of different types of traffic generated per application. The SMO classifier accounted for the highest training times with larger flow records requiring around 140.35 minutes of training 3M flows. Given the lowest reported accuracy, the algorithm performed minimal in terms of resource consumption and the reported classification results.

Considering the testing timelines, NB followed by J48 classifiers were the most efficient in classifying flows at approximately 6.3 minutes and 8.12 minutes respectively. Two-phased recorded a linear relationship between the flows tested and the respective processing time-frame. Approximately 15.17 minutes were spent in classifying 3M flows, averaging at 0.30 seconds for processing 1K flow records with a standard deviation (σ) of 0.071between 1M and 3M flows. Thus, given the high accuracy of the two-phased approach the computation performance seems highly applicable in realistic traffic classification scenarios. BN reported the highest 16.91 minutes in testing 3M flows albeit average overall classification performance as depicted in Fig. 10. The two-phased approach therefore, yields better accuracy across all traffic classes with a comparably smaller computational cost when considered in relation to the examined alternate classification approaches implemented using the WEKA platform. However, it may be noted that since WEKA is a java-based implementation of the classifiers, the exact computational overhead reported might be different when a stand-alone classifier utility for each approach is applied resulting in a more efficient performance.

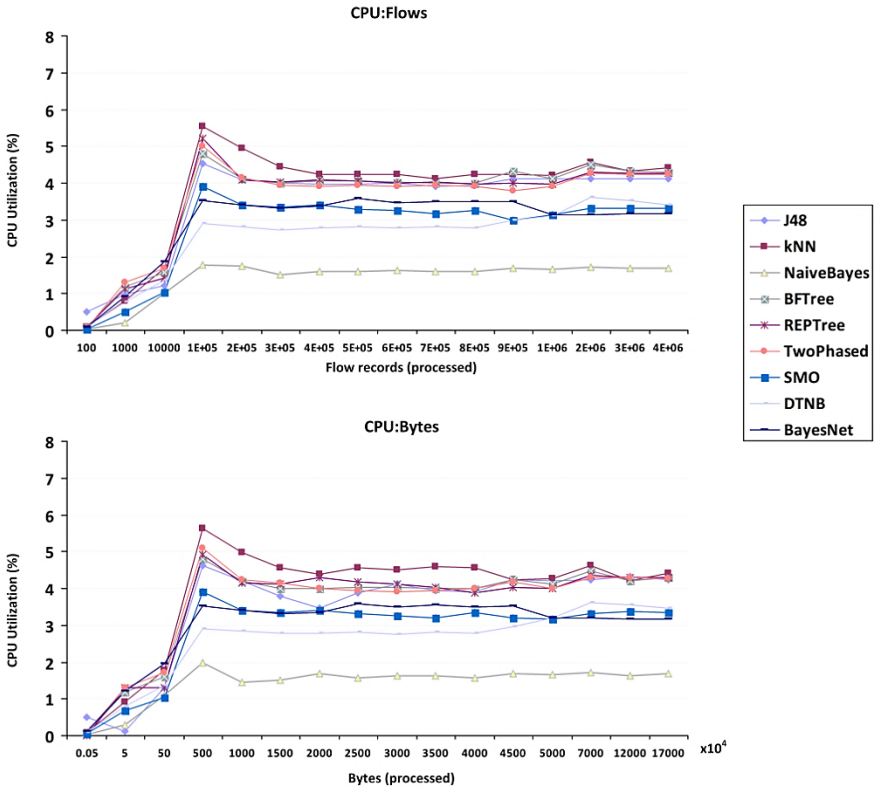


Figure 6.11. Classifier CPU Utilization (%) (a) flow records processed and (b) bytes processed

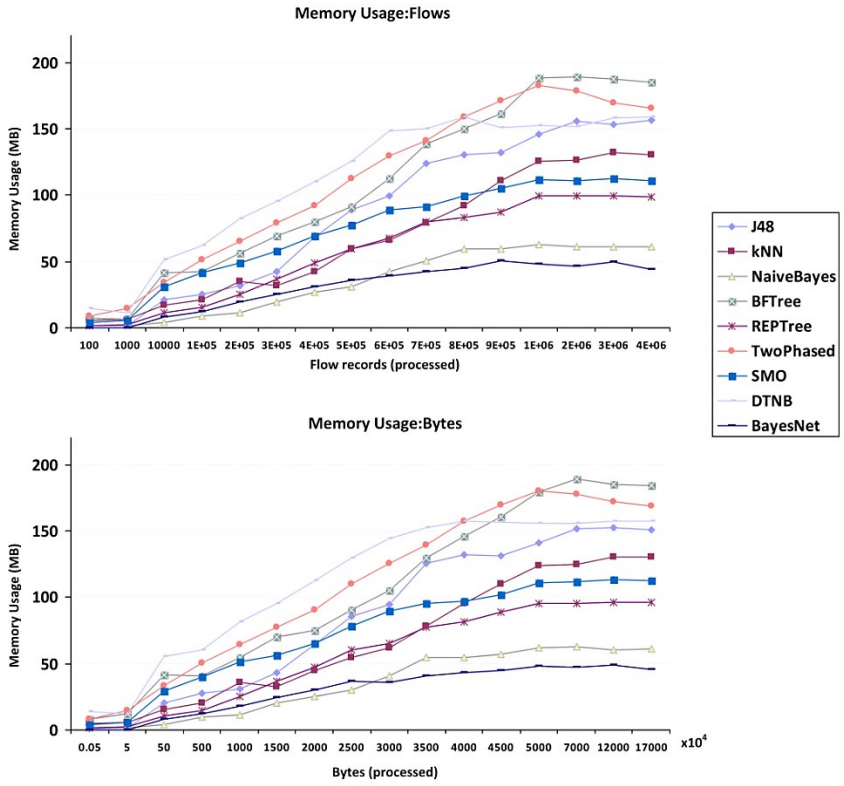


Figure 6.12. Classifier Memory Usage (MB) (a) flow records processed and (b) bytes processed

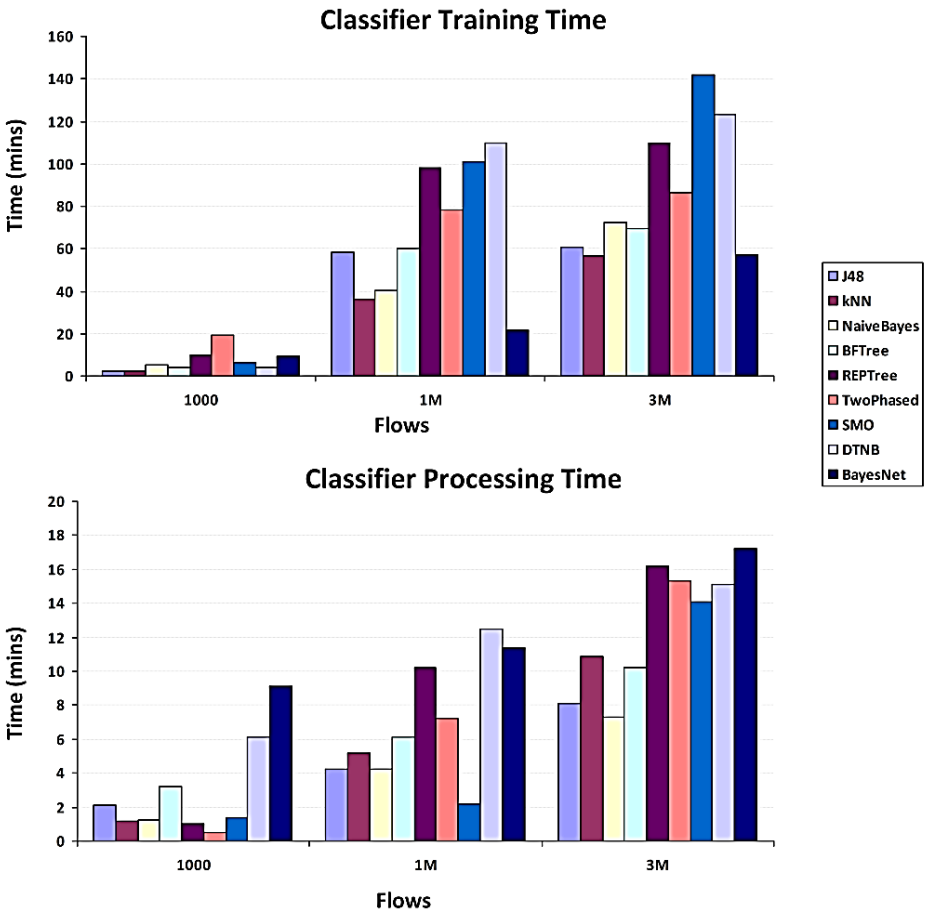


Figure 6.13. Classifier timeframes for (a) training and (b) processing time

6.6.3 Scalability

Given the classification accuracy comparisons among several classifiers, it is apparent that the prediction ability of a scheme is highly dependent on analysing a correct measure of variation between the selected flow attributes for each traffic class. Traditionally the bi-directional flow features utilized in the present research have shown considerable applicability in multiple classifiers to attain a (somewhat) acceptable degree of traffic identification. However, as highlighted in [224] and [226] the wide majority of the classification algorithms are infeasible with respect to their application in the network backbone by ISPs. The reasons for this lack of applicability range from the tremendous amount of traffic generated in the network core to the actual methodology of the approach, for example, sometimes requiring analysis of end-point behaviour for classification [226][276]. In addition flow-based techniques often rely on statistical information from bi-directional traffic (specifically TCP), and placing the traffic measurement or collection point as close to the ingress or the edge of the network as possible to collect the necessary features from outbound as well as inbound flows. An alternate approach to address this limitation is provided by

[69], which introduces an algorithm for predicting the inbound traffic flow attributes based on the unidirectional transmitted TCP flows. However, the present approach proposes using the former technique of placing flow-measurements as close to the ingress or edge of the network to corroborate the relation between upstream and downstream flows per host to generate bi-directional flow features and keep the operational and computational cost of implementing the two-phased approach to a minimal.

The proposed two-phased approach is significantly reproducible due to the utilization of NetFlow, ubiquitous in present ISP networking equipment, network edges such as residential routers in home based networks and the edge (gateway) switches in enterprise networks. Additionally, the derived classifier reported high efficiency in dealing with large data (flow records) with high level of accuracy, again a basic traffic classification requirement in user traffic profiling. The synergetic combination of classifiers, in the present case produced comprehensive traffic classification results and a comparatively lower processing overhead while using non-specialized hardware. The classifier can therefore, be put to use in the traffic classification phase during user traffic profiling resulting in greater accuracy of user trend depiction as compared to the previously used technique of IP address and port mappings based application classification.

6.7 Conclusion

The present chapter used a twofold machine learning approach for traffic classification on a per-flow basis by solely using NetFlow attributes and without depending on packet derivatives or complex time window analysis. During the unsupervised phase, approximately 6.8 million bi-directional flows for all applications were collected and cluster analysed resulting in 12 unique flow classes. The supervised phase used four different feature-sets of NetFlow attributes from the derived flow classes to test and train the C5.0 ML decision tree classifier. The foremost feature-set comprising 14 NetFlow attributes, reported an average prediction accuracy of 92.37% increasing to 96.67% with adaptive boosting. The sensitivity factor of the classifier was also exceedingly high ranging above 90% with only cloud storage flows (file upload and downloads) reporting relatively low values between 87.67% - 89.89% due to misclassification with general web browsing and streaming flows. The corresponding specificity factor, indicating classifier flow discrimination ability ranged between 98.37% – 99.57% across all applications. Furthermore, the substantive accuracy of the presented approach in achieving highly granular per-flow application identification and the computational efficiency in comparison with other machine learning classification methodologies

paves way for future work in extending this method to include other applications for real-time or near real-time flow based classification.

The following chapter investigates and evaluates the use of OpenFlow protocol features for traffic profile derivation in campus based SDN environments. The study assesses OpenFlow protocol based flow monitoring information to derive user traffic profiles for visualization of user traffic trends in campus network environments. The proposal seeks to eliminate reliance on external flow accounting methods (such as NetFlow) for recording user traffic information in larger campus environments where networking devices may be geographically dispersed and operators can benefit from a low cost centralized user profiling mechanism.

Chapter 7 OpenFlow-Enabled User Profiling in Enterprise Networks

7.1 Introduction

The OpenFlow protocol [17] provides flow monitoring and management of OpenFlow compliant SDN switches through a sophisticated set of controller to device message exchanges. The OpenFlow protocol also offers individual service improvement by guaranteeing quality of service through isolated application flow metering. Existing OpenFlow based traffic monitoring solutions are therefore, inclined towards using the protocol for flow monitoring and control, while aiming to keep the associated management overhead to a minimum. Studies such as [300], [301] and [302] have sought to establish the trade-off between resource consumption, control channel traffic load and monitoring accuracy by changing switch flow idle time out, using adaptive switch polling frequency and varying the time interval between configuration messages sent to switches. Prior work has also focused on highlighting the benefits of using asymmetric OpenFlow control messages to reduce the overall control channel overhead [303], as well as employing OpenFlow monitoring information along with anomaly and intrusion detection algorithms to harden SDN security [304]. However, no previous work has specifically focused on leveraging OpenFlow based monitoring information to profile user behaviour in an SDN framework. As evaluated in earlier chapters, user traffic profiling aims to understand real-time user behaviour and to help network administrators in visualizing user trends in subsequently implementing user-centric policies. Profiling user traffic based on application trends may more accurately express user activities and aid administrators in aligning optimization solutions to the inherent campus user classes instead of individual applications [200]. The implementation of user profiling controls, in larger campus and enterprise SDN environments, however, may require exporting flow measurements externally from dispersed network switches resulting in a substantial management overhead. The present chapter proposes profiling user application trends solely employing OpenFlow based monitoring information. The proposed approach accounts user-generated flows (application usage) towards the campus servers, using the OpenFlow counters in network switches polled via the SDN controller. Using the existing OpenFlow control channel between the edge switches and the SDN controller, flow measurement as well as profile extraction remains centralized eliminating requirement for external flow accounting (NetFlow, IPFIX, etc.) and dedicated monitoring overlays. Furthermore, the design focuses on retrieving traffic statistics nearer to the user i.e. the edge or access switches to account for any local service (or application server) traffic which may not traverse the campus core. The

extracted profiles subsequently serve as a means to characterize and monitor the campus workload. Utilizing per-profile traffic statistics, the SDN controller can anticipate real-time traffic conditions based on changing profile memberships, assisting operators in implementing user-centric policies.

To validate the feasibility of the proposed approach, the study collected traffic statistics from a virtual Open vSwitch [86] and Ryu SDN controller [70] instance connected to a realistic campus edge to profile user activity. User statistics were monitored over a two-week time frame and subjected to unsupervised k-means cluster analysis to segregate users into different classes based on their application trends. The scalability of the design was further evaluated by simulating several user profile loads in Mininet [103] to benchmark the monitoring message overhead as well as the computational cost associated with user profiling.

The remainder of this chapter is organized as follows. Section 7.2 details the proposed user profiling method using OpenFlow protocol. Section 7.3 discusses the derived profiles, also highlighting the scalability evaluation of the design. Section 7.4 gives a perspective on profiling based traffic engineering and final conclusions are drawn in section 7.5.

7.2 Design

The proposed traffic profiling methodology comprises of two main components (i) OpenFlow traffic monitor and (ii) the traffic profiling engine.

The *traffic monitor* utilizes five primary OpenFlow message types presented earlier in Table 2.3 to record the individual application usage of users connected to an OpenFlow compliant switch (such as Open vSwitch) [Appendix – 5.5]. The resulting monitoring information collected per flow is a seven-tuple record including the source and destination IP address and ports, duration of the flow, the number of packets matching the flow and the total bytes transferred before flow termination <SrcIP, DstIP, SrcPort, DstPort, Duration, Packets, Bytes>.

Following record collection, the *profiling engine* collates traffic composition statistics per user as a percentage of user generated flows towards campus data sources, mapped according to their respective destination IP address(es). The aggregate traffic composition vectors are afterwards fed to a k-means clustering module, segregating users into different classes (profiles) based on their application trends. The resulting profiles are stored in a central database and continuously

monitored to benchmark their stability with any deviation from pre-determined baseline values triggering re-profiling [Appendix – 2.4]. The following sub-sections discuss the data collection setup, the traffic monitor and the profiling engine in detail.

7.2.1 OpenFlow traffic monitor

To determine the feasibility of present traffic profiling approach, traffic records were collected from a realistic academic network segment consisting of approximately 42 users in the computing and engineering departments over a two week duration between 15/02/2016 and 29/02/2016. Each user had a single computer, being used to connect to campus application servers. In order to eliminate the impact of this study on production traffic, the setup used a Linux monitoring machine (VM1) running an Open vSwitch (SW1) and Ryu SDN controller instance connected to the departmental LAN as shown in Fig. 7.1. Port monitoring was enabled at the default gateway (SW2) to replicate all traffic to and from each user to the VM1 interface (virtual switch SW1). The mirrored traffic was processed through the Open vSwitch (SW1), however, not forwarded to any outside port, since the objective was solely the collection of user traffic statistics. The traffic monitoring application running on VM1 polled Open vSwitch (SW1) counters by issuing RESTful calls to the Ryu controller to collect per user flow statistics. All user machines used static IP addressing scheme to simplify accounting per user application usage from the collected OpenFlow records. Steps describing the installation of flows in SW1, their subsequent updating, and user statistics collection are detailed as follows.

1) Flow installation: Standard Ryu based layer3 routing function and the traffic monitor application was implemented using the default OpenFlow behaviour with customized flow routing as shown in Fig. 7.2. The first packet of incoming (mirrored) traffic on SW1 port1, was matched against existing table0 entries for processing. In case of a *table_miss*, an OpenFlow *packet_in* message consisting of the first packet of the flow was created and sent to the controller. On receiving *packet_in*, the controller created a *packet_out* message instructing SW1 to forward upstream LAN traffic via OpenFlow table1 and downstream traffic (from campus servers and the internet) via table2 out port2. Since, the purpose of the experiment was data collection and not actual flow forwarding, and OpenFlow does not prevent flow installation towards a blocked port, virtual port2 on SW1 was set to blocking mode (sink). This resulted in the installation of respective flows in SW1 with subsequent flow packets negotiating table1 or table2 out port2, without consequences for live user traffic and generating per user flow statistics. The Open vSwitch SW1, therefore, installed

and updated OpenFlow entries in each flow table as would be the case if directly connected as the LAN default gateway to forward user traffic.

2) Statistics collection: The traffic monitor made RESTful calls to the Ryu controller to determine the statistics for table1 and table2 entities. The controller, in turn, fulfilled these polling requests by issuing OpenFlow *flow_stats* and *table_stats* messages to SW1, with the respective counter for each flow and table entry sent to the traffic monitor. Since RESTful is a non-subscription based API, the polling frequency of RESTful calls was manually set to 30 seconds, approximately half of the default *idle_timeout* value (60 seconds) to regularly generate statistics. In addition to frequent polling, flow completion and *idle_timeout* expiration triggered asymmetric *flow_rem* event message by SW1 to the controller, in turn updating the traffic monitor. The monitor collected per user seven-tuple record entries, collated every 24 hours and fed to the profiling engine to extract user profiles. The profiling engine design is discussed in next subsection.

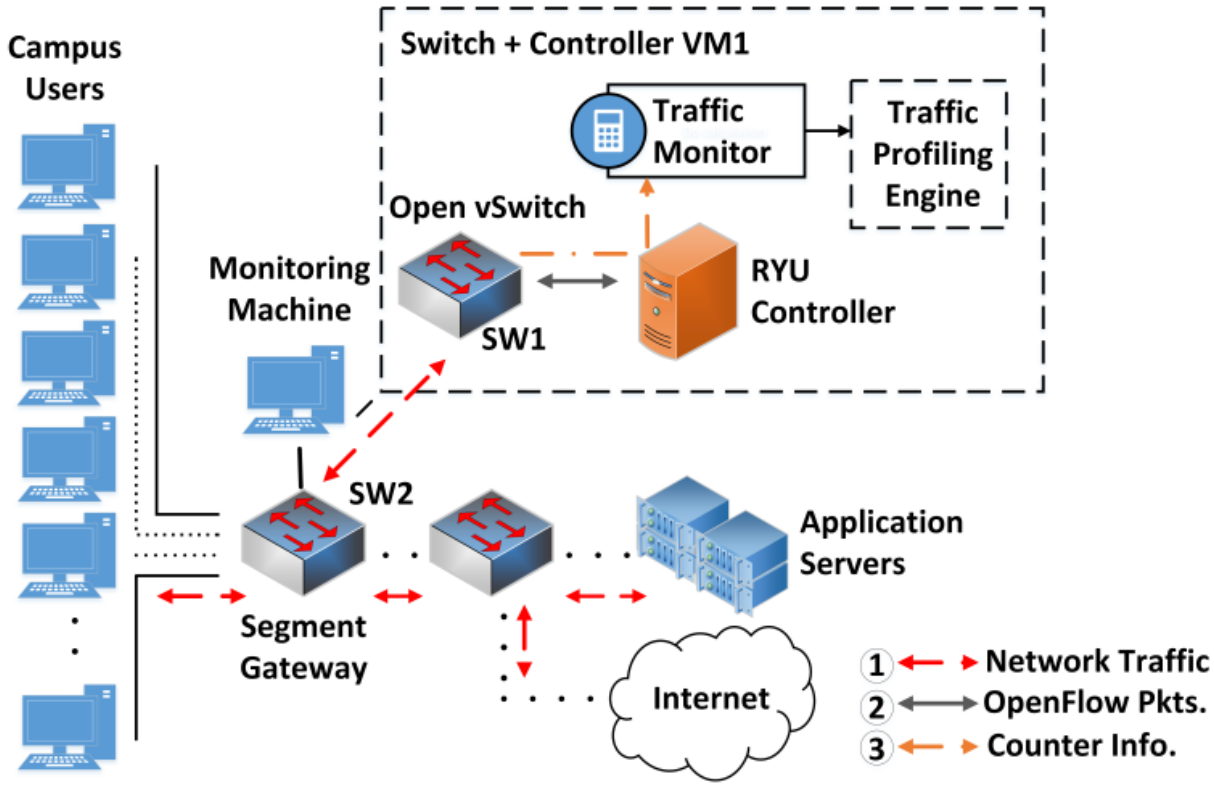


Figure 7.1. Data collection setup: campus network segment

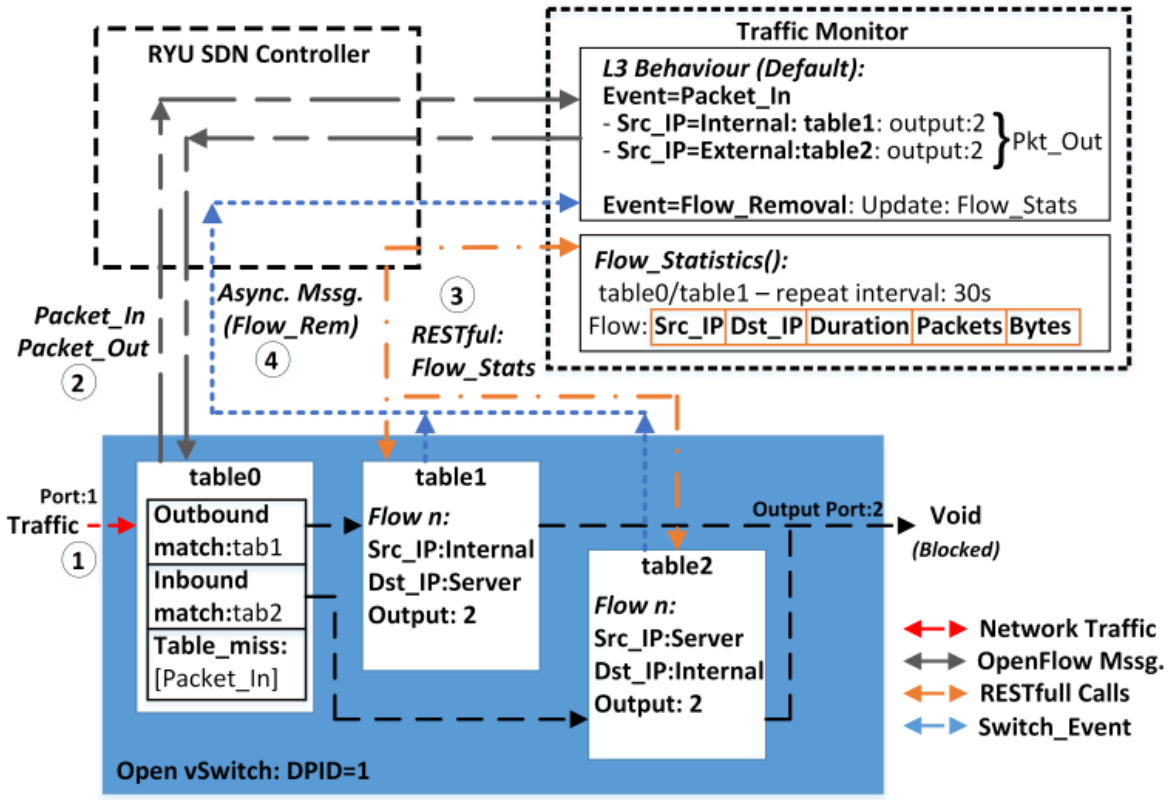


Figure 7.2. Traffic monitoring schematic

7.2.2 Traffic profiling engine

The profiling engine design is depicted in Fig. 7.3. User traffic collected by the traffic monitor was classified by matching seven-tuple traffic records against source and destination IP addresses and ports used by the respective users and campus servers [Appendix – 1.3]. To further account for replication in nature of user activities, and derive meaningful profiles, services were tiered into distinct categories depicted in Table 7.1. A unique webpage visit or service usage on a user machine could therefore, be defined by the vector u_i given in Eq. 7.1. In Eq. 7.1, each entity represents the percentage of user flows generated towards the application tiers given in Table 7.1.

$$u_i = [e_i, g_i, v_i, c_i , p_i, h_i, r_i, w_i , z_i] \quad (7.1)$$

In equation (7.1) above, *i* uniquely identifies the user machine and the remaining entities represent the service usage percentage in accordance with Table 7.2. Network activity for a user u_1 over any given 24 hour time-bin, e.g. [29/02/2016], could therefore be represented by the application distribution in Eq. 7.2.

$$u_{1\ [29/02/2016]} = [43.2\ 15.1\ 0.2\ 9.6\ 4.1\ 2.1\ 17.4\ 4.4\ 2.9] \quad (7.2)$$

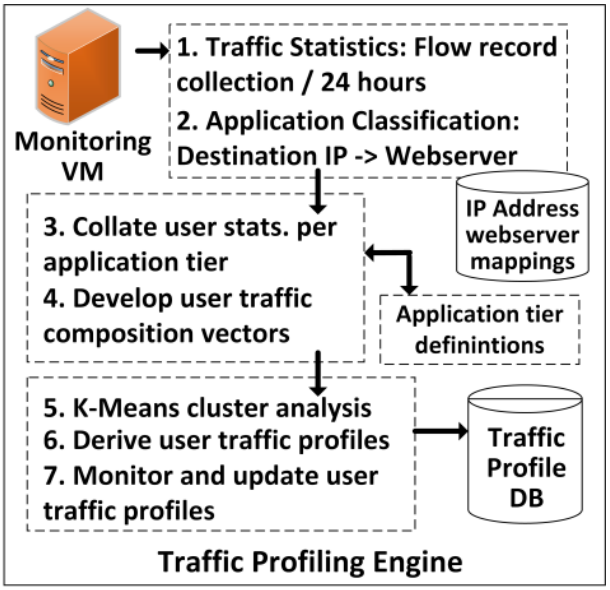


Figure 7.3. Traffic profling engine

Once application distribution vectors per user machine were collected, the traffic profiling engine implemented an R programming library of the Hartigan and Wong k-means function [18], to extract user classes based on the application trends as used in earlier chapters (Eq. 3.1). Furthermore, to benchmark the stability of the profiles, user profile transitions were evaluated every 24 hours over the two weeks of study. The extracted user profiles, profile stability evaluation, and computational cost of the design are described in the following section.

Table 7.1. Application Tiers

Application Tier	Website, Destination Port
Emailing (e)	Outlook, SMTP, POP3, IMAP
Storage (g)	Central storage (://Z Drive, FTP)
Streaming (v)	Podcasting, video content
Communications (c)	Office communications server
Enterprise (p)	Corporation information system, staff portal
Publishing (h)	Content management system (document, print)
Software (r)	Software distribution service
Web browsing (w)	External Internet traffic
Network utility (z)	DNS queries, Network Multicasts

7.3 User traffic profiles

A total of approximately 7.8 million records were collected over the two week study and the corresponding user traffic composition vectors were afterwards subjected to k-means clustering. The plot of *wss vs. k* of the user traffic composition vectors is given in Fig 7.4. The profiling engine calculated the maximum within-cluster variance between each successive value of k, examined up to k=20 to evaluate the optimal cluster number. As shown in Fig. 7.4, the variance between individual values is maximum until k=6, however, subsequent values of k (≥6) show minimum change in the successive overall variance (<0.05%). Therefore, for the present study, k=6 provided an optimal number of user profiles fitting the sample space used for further analysis. The profiling engine correspondingly marked the daily user traffic records with the individual cluster (profile) colour. The next subsection examines the resulting six user traffic profiles.

7.3.1 Extracted profiles

The extracted user traffic profiles (for clusters k=6), highlighting the application trends as a percentage of user generated flows are depicted in Fig. 7.5. From a monitoring and network management perspective, the derived user profiles showed significant variation in activities among the derived traffic classes. For example, Profile 1 concentrated mainly on web browsing (39%) with relatively limited usage of other applications apart from the corporate information (20.5%) and content management services (12.4%). Profile 2 focused on using office instant messenger and VoIP largely (64.5%) with limited use of content management applications and web browsing (12.2%). In comparison with other profiles, Profile 3 users heavily interacted with corporate information services (50.3%) with a significant use of email service (10.1%). Profile 4 users concentrated on document utilities and print content creation (57.7%) as well as using centralized storage (11.3%).

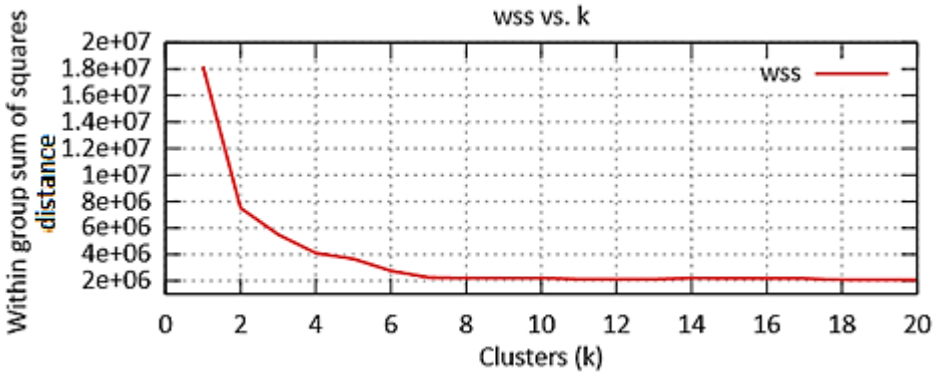


Figure 7.4. Optimal cluster determination – wss. vs. k

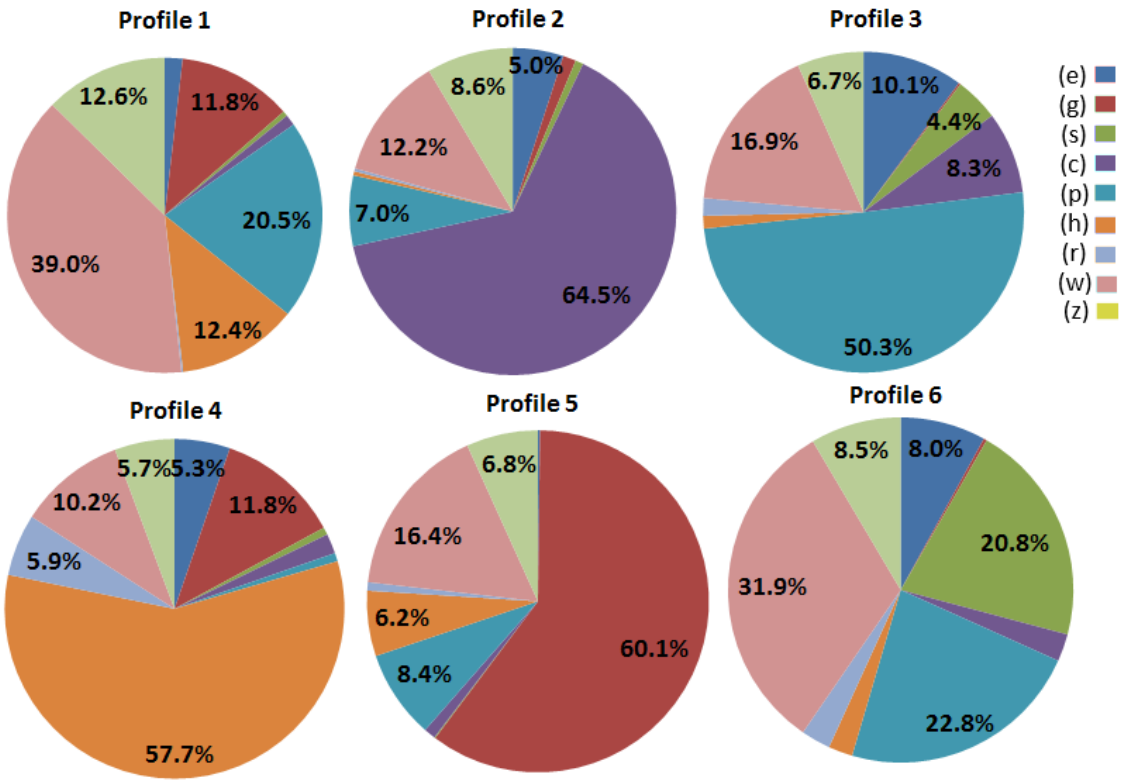


Figure 7.5. User traffic profiles

Profile 5 mainly used central storage filer (60.1%) with small use of content and corporate information server. Profile 6 was a mix of web browsing, email usage, file storage and the staff portal along with streaming (20.8%). Each of the derived campus user profiles, therefore, represented a significant discrimination towards a certain mix of applications and services. The use of software distribution was, however, significantly low compared to other applications among all user profiles with profile 4 showing the highest proportion of software downloads (5.9%) from the campus software store. To benchmark the traffic baseline for each profile, the maximum probability for the number of users, total traffic volume along with upstream and downstream flow rates and flow statistics was calculated and is given in Figs. 7.6-7.8. Profile 1 had the highest number of users (10-14 users) during office hours (09:00-17:00hrs) followed by profile 3 (6-8 users) while profile 6 membership increased during the evening. Despite having the lowest number of users (1-5), profile 6 accounted for the greatest traffic volume, primarily due to the greater usage of streaming application in this traffic class compared to other profiles. Minimum profile memberships (active users) were recorded between 03:00-06:00hrs. Fig. 7.8 represents the corresponding upload and download rate per user profile including per application and consolidated average data rates (x). In terms of individual application tiers, storage (g) had the highest upstream and downstream rates (4-5Mbps), followed by streaming (s) downloads (up to 5Mbps). Web browsing had the

minimum data rate footprint for both upstream (0.2Mpbs) as well as downstream (0.6Mpbs) traffic. The minimum flow rate was due to web browsing generating low overall speeds, particularly when using an HTTP1.1 connection (so the connection remains open between pages or the browser sends *keepalives* for a while after the actual data transfer finished). The average data rates (x) remained consistent across all profiles ranging between 1-1.5Mbps for the upstream compared to 1.8-2Mbps on downloads. The corresponding inter-flow arrival times per profile (for active users) on an hourly basis are given in Fig. 7.8. Profile 1 had the highest amount of flows generated and received (240-260 flow) per hour for active users, again due to the greater profile membership attributed to this user class. The lowest flow generation was for users in profile 2 (80-100 flows) mainly constituting communication service usage. Similarly profile 4 had the minimum inter-flow arrival duration (575ms) for transmitted flows, showing quick use of print services when active. Profile 6, concentrating on streaming had the minimum inter-flow arrivals for downstream traffic (275ms) mainly attributed to dynamic download of streaming content from multiple sources i.e. load-balanced video servers. In view of the discriminative application trends, profile memberships and associated flow measurements for the evaluated campus network segment depicted in the derived user profiles, operators may want control over which users to prioritize in terms of bandwidth allocation as well as select optimal routes for resource intensive profiles. An overview of integrating profiling based controls in campus SDN is discussed further in section 7.4.

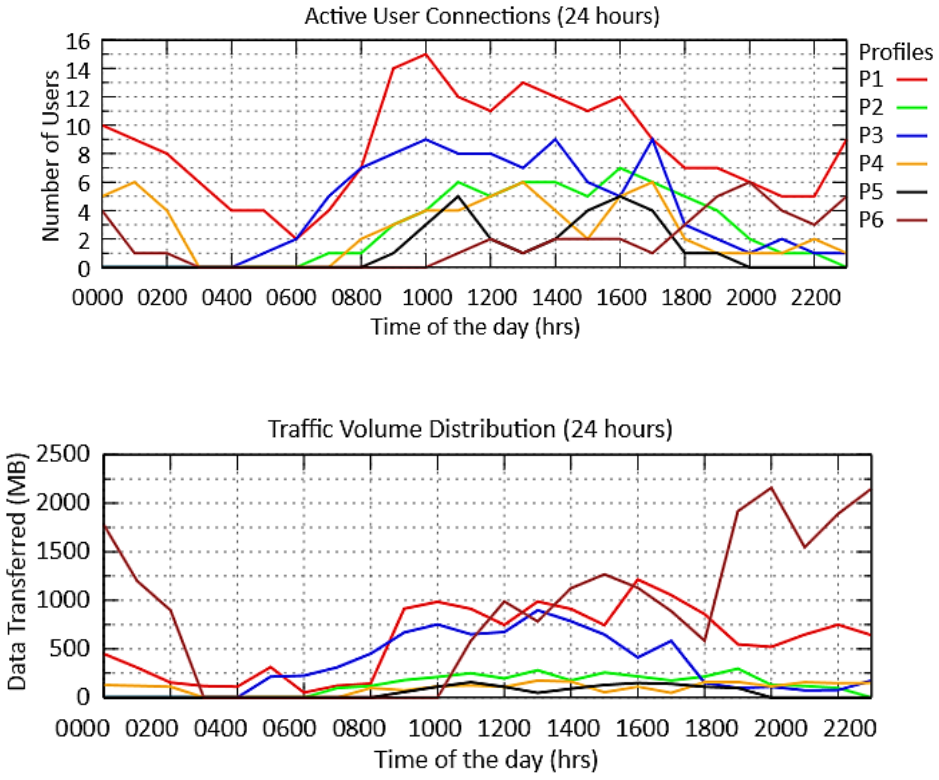


Figure 7.6. Probability distribution: (a) profile memership and (b) traffic volume

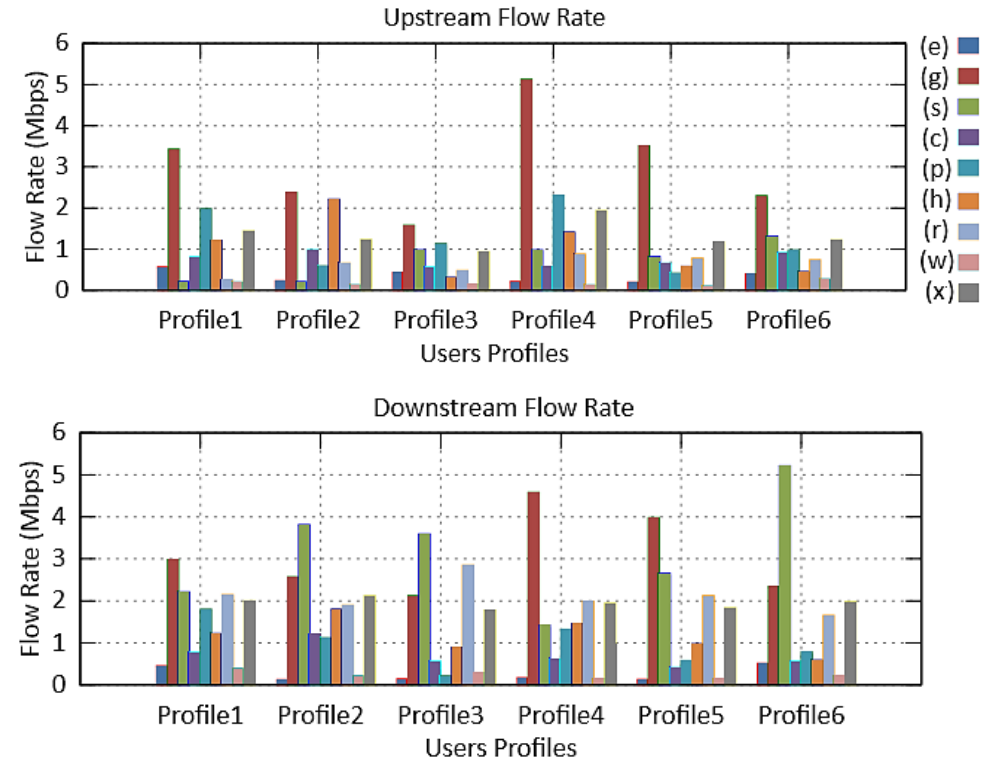


Figure 7.7. Flow transfer rates: (a) upstream traffic and (b) downstream traffic

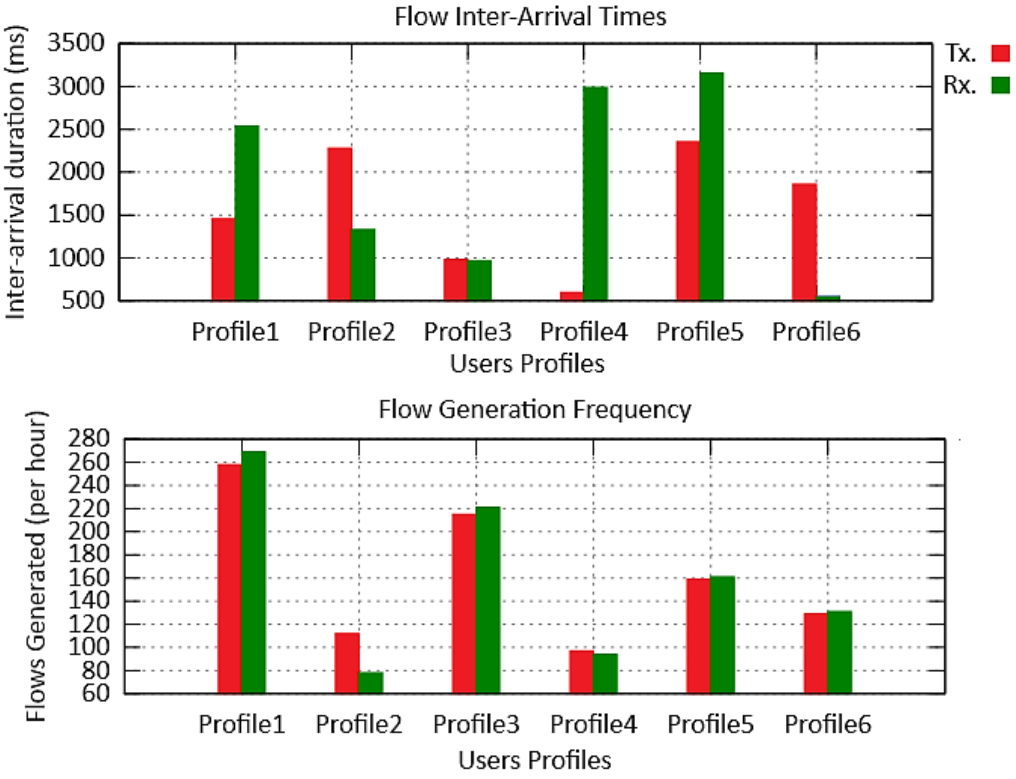


Figure 7.8. Flow statistics: (a) flow inter-arrival time and (b) total flows (hourly)

7.3.2 Profile stability

Profile consistency highlights the significance of gaining a better insight to changes in user activity as well as benchmark the stability of the extracted profiles and re-profiling frequency. Therefore, to evaluate user profile retention, the average probability of profiles change for the same users for each subsequent day of study was computed and is presented in Table 7.2. Profile 5 users showed the highest consistency in retaining profiles at 99.1% followed by profile 4 at 99% while profile 6 showed the lowest at 96.1%. The reported profile retention of campus users was greater in comparison with a similar study (chapter 4) aimed at evaluating profile stability for multi-device residential users reporting the lowest profile consistency at 81% [293]. Campus users hence showed a significantly greater degree of consistency in daily application usage in relation to residential users. The probability of a profile gaining or losing a device every 24 hours is also given in Table 3. Profile 1 had the highest probability of gaining users (93%) profile 6 had highest probability of transitioning users (80%). The average probabilities of inter-profile transitions every 24 hours are given in Table 7.3. Profile 6 users showed a tendency (up to 3%) to transition to profile 1, the primary difference between the two profiles being proportional changes in streaming and publishing tier respectively. Similarly, profile 1 users tilted towards profile 3 (1.1%) having greater corporate information system and staff portal usage. Profile 4 with heavy publishing inclined towards profile 1 (at 0.6%) having higher web access. It was therefore, noted that where users transitioned to a different profile, it was always to profiles having somewhat similar application usage ratios to their own. Inter-profile transitions were mainly due to proportional variation in the same kind of user activity rather than a complete change of user roles, increasing the applicability of derived profile baseline in campus network monitoring.

Table 7.2. Average Probability of Profile Change (/24 Hours)

User Profiles	Probability of No Change	Probability of Change		
		Change:	***Gain***	***Loss***
Profile 1	0.981	0.019	0.93	0.07
Profile 2	0.970	0.03	0.44	0.56
Profile 3	0.985	0.015	0.92	0.08
Profile 4	0.990	0.01	0.55	0.45
Profile 5	0.991	0.009	0.49	0.51
Profile 6	0.961	0.039	0.20	0.80

Table 7.3. Inter-Profile Transition Probability (/24 Hours)

User Profiles	P1	P2	P3	P4	P5	P6
Profile 1	0.981	0.001	0.011	0.002	0.004	0.001
Profile 2	0.009	0.970	0.017	0.001	0.001	0.002
Profile 3	0.008	0.001	0.985	0.003	0.002	0.001
Profile 4	0.006	0.001	0.001	0.990	0.002	0.001
Profile 5	0.001	0.003	0.001	0.002	0.991	0.002
Profile 6	0.03	0.0091	0.001	0.0004	0.0003	0.961

7.3.3 Profiling computational cost

To evaluate the computational cost of the traffic profiling mechanism, memory and CPU utilization were recorded during the profiling workload completion. The purpose of this exercise was to appreciate the amount of computational resource needed in profiling user traffic from a practical campus network setting. The test machine (PC) used an Intel based i54310-M processor chipset with two CPUs, each at 2.70 GHz and 16GB of RAM. The operating system used a GNU/Linux kernel (3.14.4 x64) and it was verified that no other user processes (apart from the profiling engine) were consuming CPU cycles or any of the inherent operating system processes were CPU or I/O intensive. Fig. 7.9 illustrates the memory and CPU utilization vs. the number of records processed. The initial spike observed in CPU and memory utilization during start-up was followed by a brief linear curve for both resources in relation to the number of flow records processed. However, with continued increase in the number of records (≥1 million records) memory utilization reached a steady-state pattern having a maximum observed value of 335MB. CPU utilization on the other hand continued to increase with maximum value of 41.63% for the total 7.8 million records. Similarly, the time duration involved in processing the records is given in Fig. 7.10.

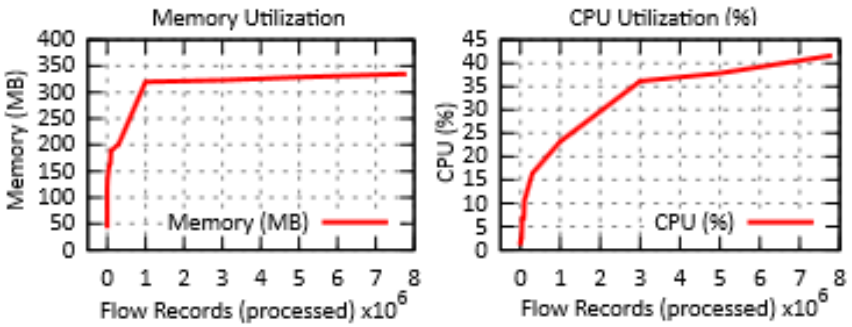


Figure 7.9. Profiling overhead: (a) memory and (b) CPU utilization

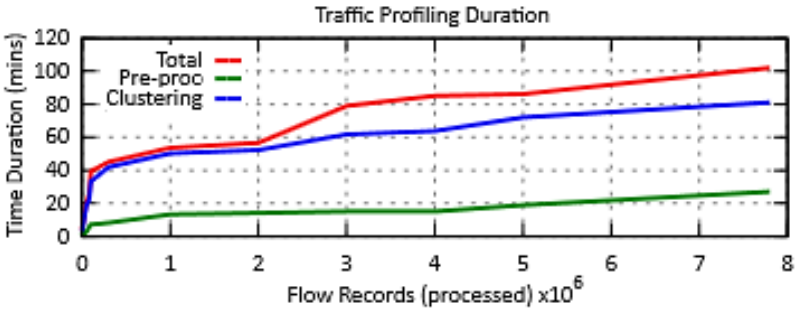


Figure 7.10. Traffic profiling duration vs. traffic records processed

As evident from the graph a substantial portion of the total time was spent in clustering compared to pre-processing (collating) per user statistics. The total duration for processing 7.8 million records was approximately 103 minutes. The observed CPU and memory footprint required in processing an order of $x10^6$ monitoring records highlight the viability of the proposed profiling mechanism in an online campus implementation. A dedicated server with relatively additional memory, particularly CPU power may be employed for profiling which may further expedite the clustering process and reduce the total profiling duration.

7.3.4 Control-channel overhead

In addition to the profiling resource computation cost, it is important to consider the traffic workload added to the OpenFlow control channel as a result of the statistics collection required for traffic profiling. To evaluate the load attributed to the control channel due to the proposed customization i.e. profiling traffic from an edge switch, the experimentation workload was emulated in Mininet using Ostinato traffic generator utility [205]. The analysis of the workload accounted (i) the monitoring information required for traffic profiling including the *packet_in*, *packet_out* and *flow_rem* messages, and (ii) the polling of flow tables via *flow_stat* and *table_stat* messages at regular 30s intervals. Fig. 7.11 presents the topology and the related traffic simulation parameters are given in Table 7.4. The topology comprised of 12 user machines, six representing each of the derived profile users and the remaining six sourcing campus server traffic. The traffic load was gradually increased starting from 10 users per profile up to a maximum of 100 users per profile to measure the control channel overhead generated by the edge switch. Employing the default OpenFlow behaviour, *packet_in* messages included the first complete packet of incoming flows as opposed to the alternate option of buffering the packet in the switch and sending *buffer_id* with routing request to the controller which requires considerably greater switch memory [17]. Using default OpenFlow option ensured the evaluation scaled to typical switch configuration. The resulting control channel traffic with varying workload is given in Fig. 7.12. The bulk of the traffic

comprised of flow control *packet_in* and *packet_out* messages from the controller with minimum traffic attributed to statistics collection (*flow_stat*, *table_stat*, *flow_rem*) messages. This was primarily due to the relative size of *packet_in* and *packet_out* messages compared to counter polling messages. At the maximum user load of 600 users (100 users per profile), a total of 697 upload packets and control traffic rate of 326kbps was observed. On the downstream, the packet rate remained lower due to absence of switch-controller *flow_rem* messages, peaking at 676 packets. Downstream traffic rate was approximately 353kbps suggesting swifter processing on the controller side than upstream. The present scenario considered the messaging overhead of traffic monitor in addition to the forwarding control messages, presenting majority of the edge switch bound control traffic. Any additional flow control traffic, i.e. *flow_mod* messages sent to intermediate campus switches, would be distributed depending on the underlying network topology. For an edge switch catering to approximately 600 users, the maximum bi-directional packet overhead (4.02%) and control traffic rate (4.96%) due to flow statistics collection alone poses no significant impact on existing OpenFlow channel traffic. Operators may therefore, utilize the existing network fabric (depending on capacity) to monitor edge switch user traffic from a central controller without requiring additional monitoring overlay. The next section highlights some of the applications of the proposed OpenFlow traffic monitoring solution.

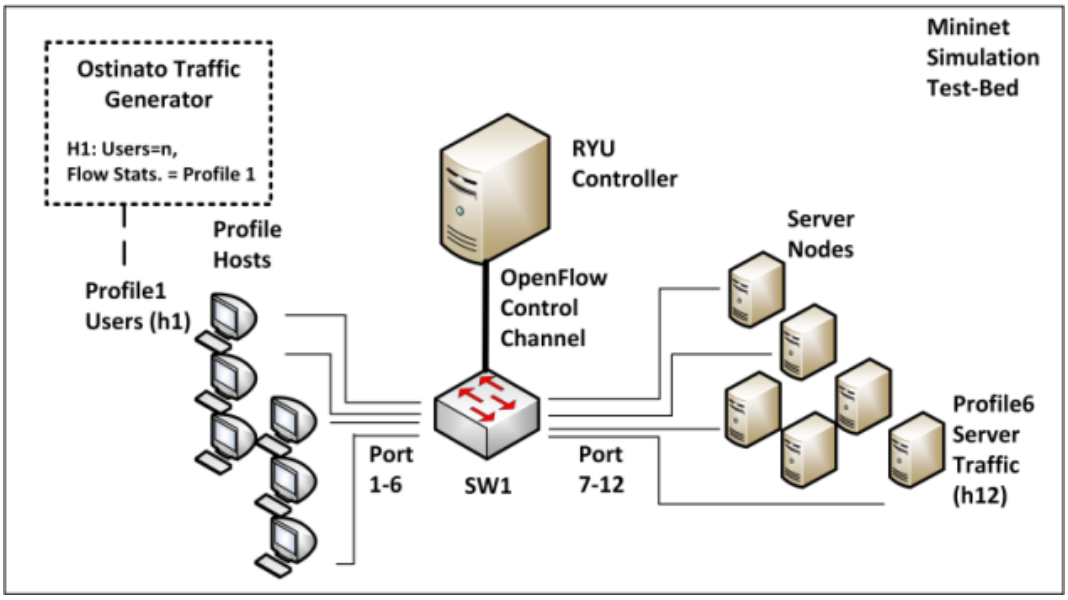


Figure 7.11. Control channel overhead evaluation – Mininet topology

Table 7.4. Traffic Configuration Parameters of Simulation

Parameter	Value	Remarks
SDN related	OpenFlow: v1.4	Default behaviour; idle_timeout 60s; traffic monitor polling 30s
	Open vSwitch: v1.3.1	
	Ryu Controller: v3.3	
	Mininet: v2.21	
	Ostinato: v0.7.1	
Workload	10-100 users per profile	Min: 60, Max: 600 users
Runtime	15 minutes per workload	-
Flow duration	5.61-31.13s	Source: user profile flow statistics
Flow frequency	190-527 per hour	Source: user profile flow statistics
Packet size	64-1480 Bytes	Random variation by Ostinato generator

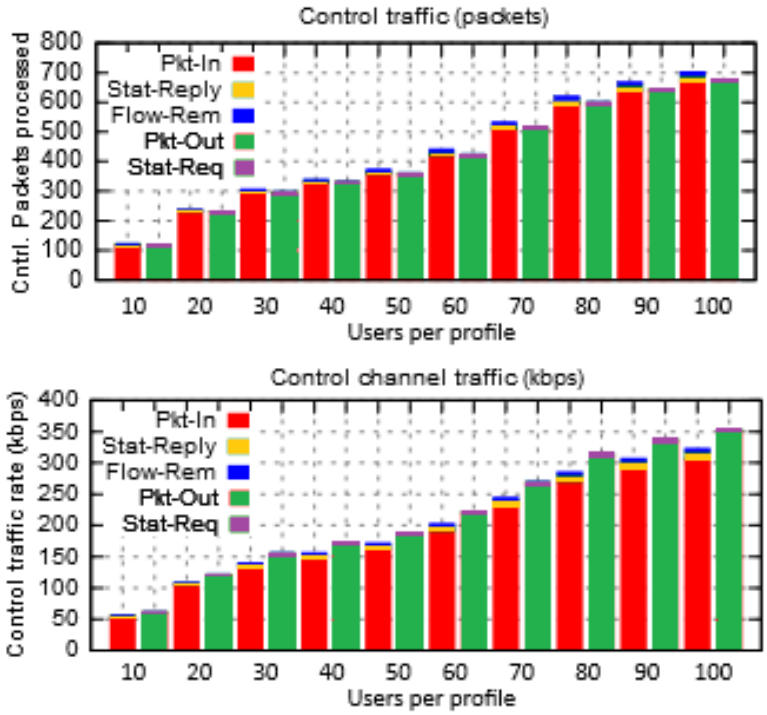


Figure 7.12. Control channel (a) control packets (b) control traffic rate (kbps)

7.4 Application: campus traffic management

The extracted user traffic profiles from the campus network segment represent varying user application trends, giving network administrators an intuitive means to monitor an SDN based environment. User profiling gives administrators the ability to appreciate user tendencies and design user-centric solutions rather than focusing on individual applications as well as plan for future updates. Three important avenues for integrating user profiling controls in the campus SDN framework are highlighted in this regard.

1) Real-time network monitoring: User traffic profiles may provide a real-time visualization of user activity to monitor the campus network. The six extracted profiles in Fig. 7.5 showed considerable stability and consistency. Baseline of traffic profiles depicted in Fig. 7.6 – 7.8 including the time of the day profile memberships, traffic volume, the respective flow rates as well as flow generation frequency may aid the network administrator in monitoring the campus traffic in real-time via the proposed traffic monitor. Additionally, baseline statistics associated with each profile could serve as an input for timely anomaly detection, with any variation from anticipated trends triggering an alarm as well as serve as an indication for re-evaluation of the derived profiles.

2) Link management: The extracted profiles assist in the identification of resource heavy from lighter profiles. Implementation of a profile optimization scheme may allow operators to rate-limit as well as balance selected profile traffic on the available links between several departments. A similar profile prioritization and per profile traffic queueing approach tested in residential SDN to rate-limit user to service provider traffic in chapter 5, yielded greater bandwidth availability for high priority users under network congestion [305]. Furthermore, profile prioritization may also allow improved external campus-data center route selection to minimize server switch (ToR) oversubscription effects on priority users.

3) Energy conservation: A growing number of energy conservation techniques in SDN rely on switching off network components using customized controller-switch OpenFlow implementations. Determining which device subsets to dynamically switch off, as well as consolidating virtual machines to minimize active server instances, however, remains challenging [306]. Time of the day variation in profile membership, and flow statistics offers enhanced user traffic visualization which may aid operators in reducing energy consumption at the network and server level. Using profile statistics, operators could

design optimal server placement algorithms according to real-time resource requirements and in tandem reduce the number of active devices (and ports), to conserve energy through efficient network provisioning.

7.5 Conclusion

The present work derived six unique user traffic profiles from a campus network segment while solely using OpenFlow traffic monitoring attributes. The extracted profiles showed significant application usage discrimination among users. Furthermore, the six profiles remained largely consistent showing minimum user profile transitions over the two weeks of observation, making them viable for intuitive real-time monitoring and management of the campus SDN. Additionally, the low profiling computational cost and control channel overhead of the proposed design even at high user loads offers increased scalability for campus-wide deployment. The integration of OpenFlow-enabled user profiling controls may further allow operators to implement SDN specific user-centric traffic engineering solutions, maximize link and server utilization as well as derive energy efficient network provisioning models.

The next chapter discusses user traffic profiling in enterprise environments and presents a novel traffic management framework, using operator defined global profile and application hierarchy to dedicate network resources in data center software defined networks.

Chapter 8 User-Centric Network Provisiong in Data Center Environments

8.1 Introduction

Service providers depend on rapid application deployment to maintain business agility, requiring frequent network provisioning updates in data centers. Swift coordination of changes for service provisioning in conventional data center networking, however, is incredibly complex involving the implementation of distributed protocols on network devices to facilitate multiple services for traffic routing, switching and guaranteeing application quality of service [285]. The SDN paradigm offers automated on-demand resource allocation in data centers, a significant improvement over manually intensive conventional configuration techniques [1][2]. SDN affords state changes much faster than distributed protocols, a fundamental necessity in modern data centers [38][286]. As depicted in Fig. 8.1., using a southbound protocol, such as the OpenFlow, the centralized SDN controller can communicate with DC switches to customize real-time flow forwarding constructs [17]. Furthermore, deriving network abstraction models and subsequently allocating resources in the DC is quite frequently based around individual application requirements. Traffic measurements in data centers, however, show tremendous volatility in workload when multiple applications are hosted on the same physical or virtual fabric [5]. Both enterprise users as well as cloud subscribers may comprise of several user traffic classes representing varying application trends sharing the same data center infrastructure. Using stringent application bandwidth guarantees to optimize traffic utilizing conventional technologies such as spanning tree protocol (STP) or dynamic equal cost load balancing over multiple paths (ECMP) does not fully account for real-time application usage diversity among users often resulting in service trampling with over use of one application affecting others [287][200]. Furthermore, chained service delivery architecture of some applications necessitate communication between multiple servers to enable user request fulfilment causing traffic fluctuations, rendering per-application bandwidth allocation impractical [288]. For example, big data applications like MapReduce, requiring large data set movements, may consume a substantial portion of the available network bandwidth, leaving users frequenting basic tasks like accessing document management systems struggling for resources. Per-application bandwidth guarantees and weighted bandwidth sharing models, therefore, fail to provide operators the desired granularity to fully optimize real-time network provisioning in view of actual user workloads. Seamless application delivery in data centers, therefore, demands a more user-centric approach accounting for real-time user application trends and accurate customization

of prerequisite virtual and physical resources using SDN technology to meet user requirements. The present chapter proposes profiling user application traffic in the data center and employing the derived traffic classes to accurately assign network resource share among users. Understanding the real-time application diversity among users through traffic profiling and subsequent prioritization of profiles allows refined network policies offering balanced real-time resource distribution according to internal and external data center traffic. To this end, the present chapter contributes as follows.

1) Improving workload characterization in data centers by deriving user traffic profiles based on application trends captured using generic flow measurements and further allowing operators to define global profile and application hierarchy for computing and assigning network routing paths between service endpoints.

2) A traffic management algorithm employing the profile and application hierarchy along with anticipated profile traffic statistics in computing and assigning external traffic routes between users and front-end servers as well as internal inter-server traffic routes in the DC.

The remainder of this chapter is organized as follows. Section 8.2 gives the design overview, while the profile derivation methodology is highlighted in section 8.3 and the network management algorithms in section 8.4. Section 8.5 details the simulation environment and evaluates the proposed design with a discussion of the resulting improvements and the associated management overhead. Final conclusions are drawn in section 8.6.

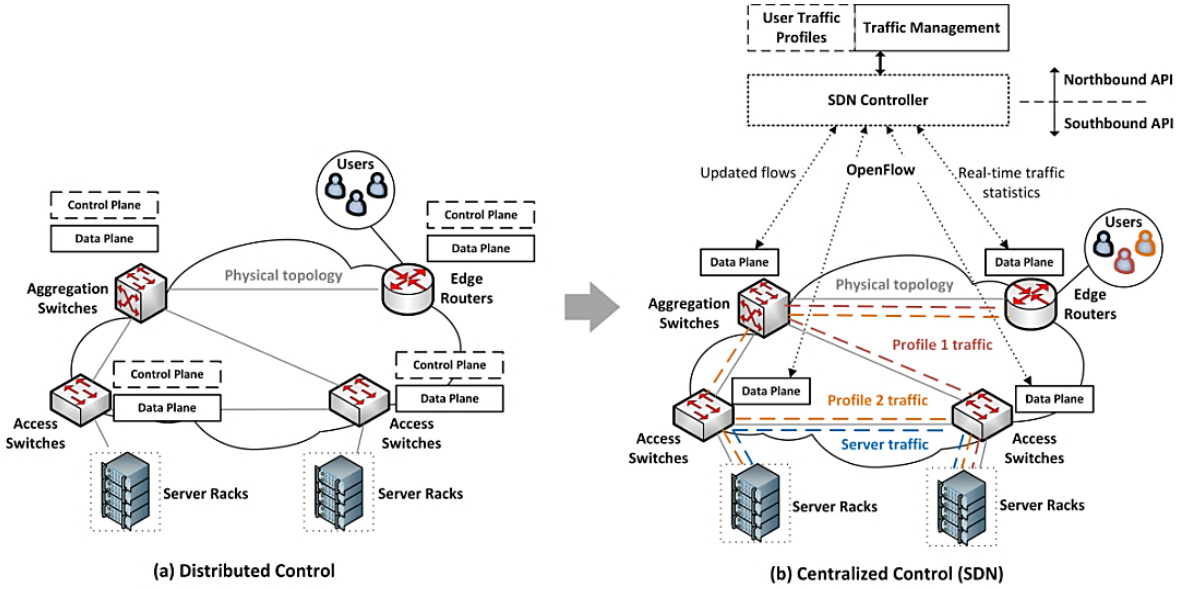


Figure 8.1. Schematic representing centralized control in SDN based DC

8.2 Design overview

The proposed design comprises of two components a) a traffic profiling scheme used to discriminate user classes based on application trends and b) a traffic management mechanism utilizing the derived profiles to define and implement network provisioning policies as illustrated in Fig. 8.2.

- The *traffic profiling scheme* constitutes the measurement and application classification of user-generated flow records (NetFlow) exported at the data center edge and subjected to un-supervised cluster analysis to segregate users into traffic classes (profiles). The extracted user profiles record application usage ratios along with anticipated user bandwidth requirements which are used by the traffic manager (via the SDN controller) in computing and provisioning network resources.

- The *traffic management algorithm* allocates real-time network resources per-profile according to operator defined user profile priority (table) while keeping track of the real-time profile memberships. External traffic routes to and from front-end application servers are computed in order of profile priority by monitoring the available link bandwidths between network edge (core) and top of the rack (ToR/access) switches utilizing the pre-logged inbound and outbound data transfer rates per profile. Internal server-server routes are computed as per a global application prioritizing scheme derived according to application usage weighting per profile, starting with the highest priority profile.

The computed flows for both external and internal traffic are installed and updated in individual network elements (access, aggregate and edge switches) using OpenFlow protocol. Additionally OpenFlow flow and table statistics serve to monitor real-time traffic, aiding the administrator in detecting anomalous (out-of-profile) traffic and determining profile regeneration frequency. Since user profiles are generated using aggregate flow exports (NetFlow) directly from the data plane (core switches), the profiling scheme does not add additional workload on the SDN controller or contribute to the existing control channel overhead. The specifics of profiling methodology and traffic management scheme are detailed in the following sections.

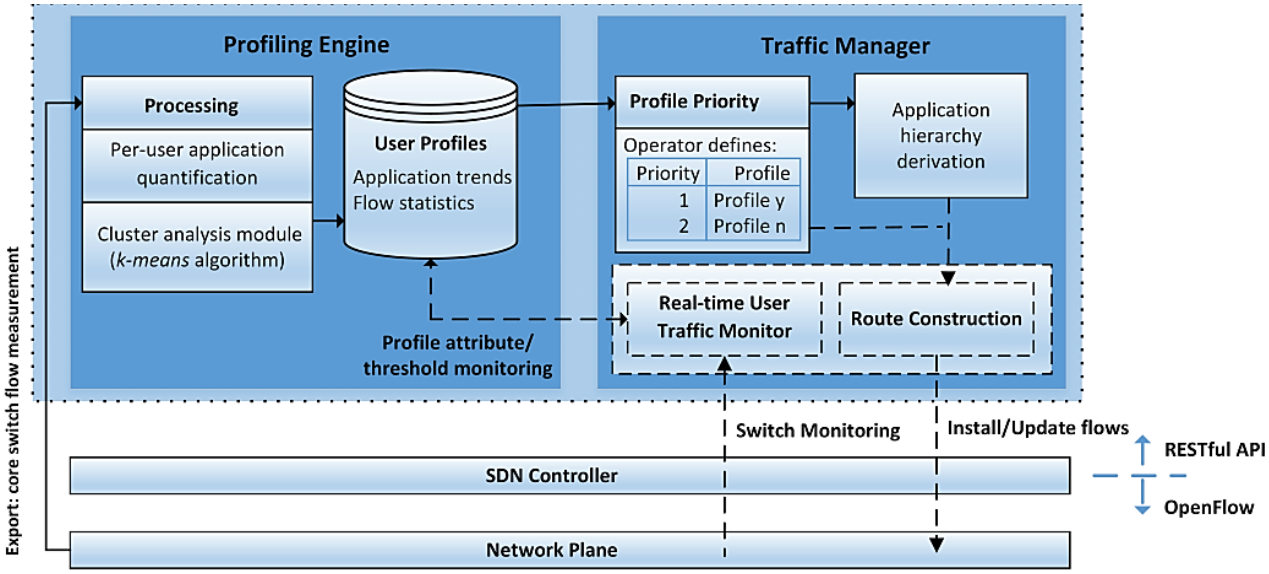


Figure 8.2. Traffic profile derivation and network management

8.3 User traffic profiling methodology

User profiling requires recording of user traffic traversing the data center network and the identification of per user flows. For this purpose, aggregate flow records are collected at traffic admission points i.e. the edge routers. Following flow collection, the application usage trends are quantized based on number of user-generated flows towards each subscribed data center application (front-end servers). To measure the total number of user flows per application, the number of flows α destined to each front-end server need to be accounted as shown in Fig. 8.3. For user flows α_s towards front-end application server (s), the total flows per application are given by $\Sigma\alpha_s$. The corresponding traffic composition vector depicting the total application usage as a function of all user u generated flows having n application subscriptions is given in Eq. 8.1.

$$u = [\alpha_1 / \sum_{s=1}^{n} \alpha_s, \alpha_2 / \sum_{s=1}^{n} \alpha_s \ldots \alpha_n / \sum_{s=1}^{n} \alpha_s] \quad (8.1)$$

Once traffic composition vectors have been derived, users need to be partitioned into groups based on proportional variation in application usage. For this purpose, the present work employs the un-supervised k-means clustering algorithm [187][189][166][293], given in Eq. 3.1. To find the optimal number of clusters (user profiles) reflecting user activities the profiling scheme uses Everitt and Hothorn technique given in [188]. The derived profiles segregate users in to different classes according to their application trends. Additionally the traffic statistics generated per profile provide a means to collect and measure per-profile bandwidth requirements.

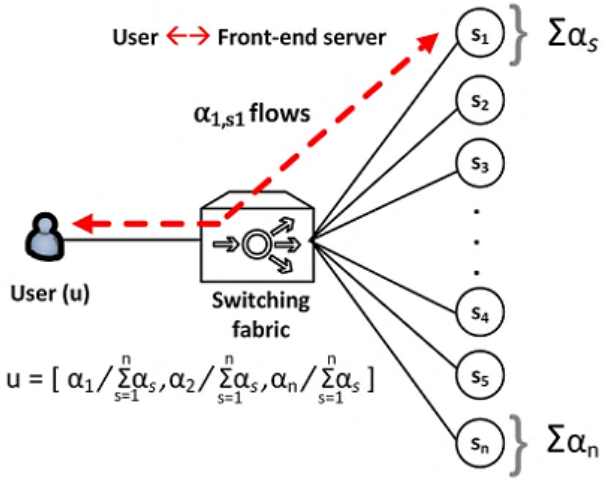


Figure 8.3. User generated traffic flows per application

8.3.1 Flow statistics

Implementing per-profile traffic policies requires determining the projected flow rates between a) users and front-end application servers per profile as well as b) internal intra-server traffic generated per application in response to each user request. A list of flow parameters used for real-time traffic management and monitoring profile stability are summarised in Table 8.1. Given the per-profile transmitted and received data transfer rate *z* for each front-end application server collected over time *t*, the maximum probability for data rate *z* to take on a given value using the density function given by Eq. 8.2.

$$\Pr [\ x \leq z \leq y\ ] = \int_x^y f_Z(z)\, dz \qquad (8.2)$$

The probability of *z* falling within a particular range of values is given by the integral of density of *z* between the lowest and greatest values of the range (x, y). The maximum probability of *z* is measured for both inbound and outbound traffic per profile for each subscribed application independently The respective data transfer rates for inbound and outbound flows for application α_i belonging to profile P_k can therefore be given by $Pr_{max}\ [z_{\ in||out}(P_k, \alpha_i)]$ and the corresponding flow inter-arrival times by $Pr_{max}\ [\Delta t_{in||out}(P_k, \alpha_i)]$. While the external traffic between users and front-end servers is relatively easy to measure and record, the internal flows generated between the application servers are subject to significant variation and greatly depend on the application logic as

well as the respective server connectivity model. A maximum threshold value is therefore, defined for the inter-flow arrival time $\Delta t_{internal}$ and the respective data rate $z_{internal}$ between internal servers per-application in response to each user (profile) connection. To evaluate the proposed traffic management scheme discussed later in section 8.5, flow rates were generated up to pre-set threshold to understand the effects of varying inter-server traffic on the viability of proposed approach.

8.3.2 Profile stability and regeneration

The baselines of network traffic per profile i.e. flow inter-transmission times and data transfer rates summarised in Table 8.1 provide an intuitive means to continuously monitor profile consistency via OpenFlow flow counters in DC core switches using multi-part *flow_stat* and *table_stat* messages. Abnormalities in anticipated aggregate flow statistics with respect to real-time profile memberships triggers as an advisory for network administrators to re-evaluate the profiles. It also dictates the efficacy of the clustering algorithm and the subsequent traffic forwarding performance. Additionally, real-time monitoring of out-of-profile traffic anomalies via OpenFlow allows dynamic management of the respective flows. The real-time monitor and traffic manager in the present context allow for a place holder profile (the guest profile) for policing out-of-profile user traffic to minimize impact on existing flows until administrators can evaluate the respective anomalies and regenerate the profiles. The introduction of new profiles or updating of existing profiles may result in operators re-evaluating network policies in view of updated requirements.

8.4 Traffic Management Approach

This section describes the proposed traffic management scheme, comprising of five procedures: profile and application hierarchy derivation, external flow management between users and front-end application servers, internal flow forwarding between application servers, installation of calculated per profile routes in individual switches (using the OpenFlow protocol) and finally the scheduling management of the respective traffic management algorithms.

8.4.1 Profile priority and application hierarchy

Conventional Ethernet uses best effort delivery of traffic which is prone to dropping of frames in face of network congestion in the data center. While technologies such as equal cost multipath (ECMP) promise higher throughput by distributing traffic over multiple links over the legacy

spanning tree protocol (STP), these alone are inadequate in policing traffic in view of the inherent mix of user classes present in the data center environment [286]. To account for the real-time traffic load and different priority flow-forwarding requirement per user profile, the present design proposes using operator-defined profile priority tables as shown in Fig. 8.4. The priority list aims to reduce the effects of network congestion for user categories (in order of hierarchy) by routing flows on different paths between the core, aggregate and access switches for external traffic between the user and application servers. Based on the application usage weighting per-profile, a global application hierarchy table is also derived. The table is used to create flow forwarding constructs using multiple routes (in order of application hierarchy) to facilitate inter-server traffic between application servers connected to different access switches. Applications higher up the chain therefore, benefit in using lesser-congested links for internal internal data center traffic. The approach translates operator defined priority per user profile to provision routes aimed at increasing throughput and reducing the effects of network congestion, on not only external but also internal flows which form the bulk of traffic within the data center. For example, resource intensive profiles having higher business productivity may be placed at the top priority while the guest profile comprising of out-of-profile and anomalous user traffic placed at the bottom. The proposal allows operators greater leverage in defining network provisioning policies according to real-time user application trends captured in user profiles instead of relying on isolated applications and services.

Table 8.1. User profiles and inter-server flow parameters

Entity	Parameter	Usage	Technology Implementation
User traffic profiles	Flow rate (inbound and outbound) $z_{in \,||\, z_{out}}$	*Aggregate value:* Real-time profile monitoring *Per subscribed application:* External route construction	User traffic profiling: NetFlow: core switch export Real-time monitoring: OpenFlow: *flow_stats, table_stats* message Route construction: OpenFlow: *flow_mod* message
	Flow arrival (inbound and outbound) $\Delta t_{in \,||\, \Delta t_{out}}$		
Application servers	Inter-server data rate $z_{internal}$	Internal route construction	
	Inter-server flow arrival threshold $\Delta t_{internal}$		

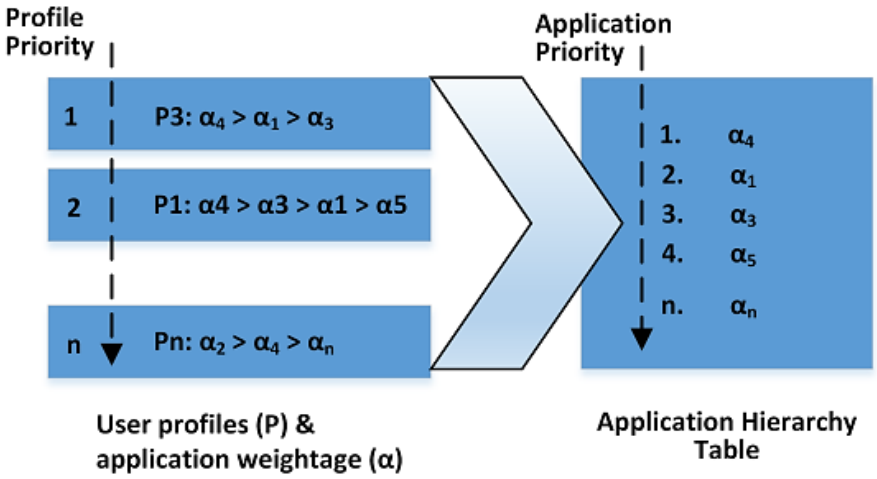


Figure 8.4. Profile and application hierarchy

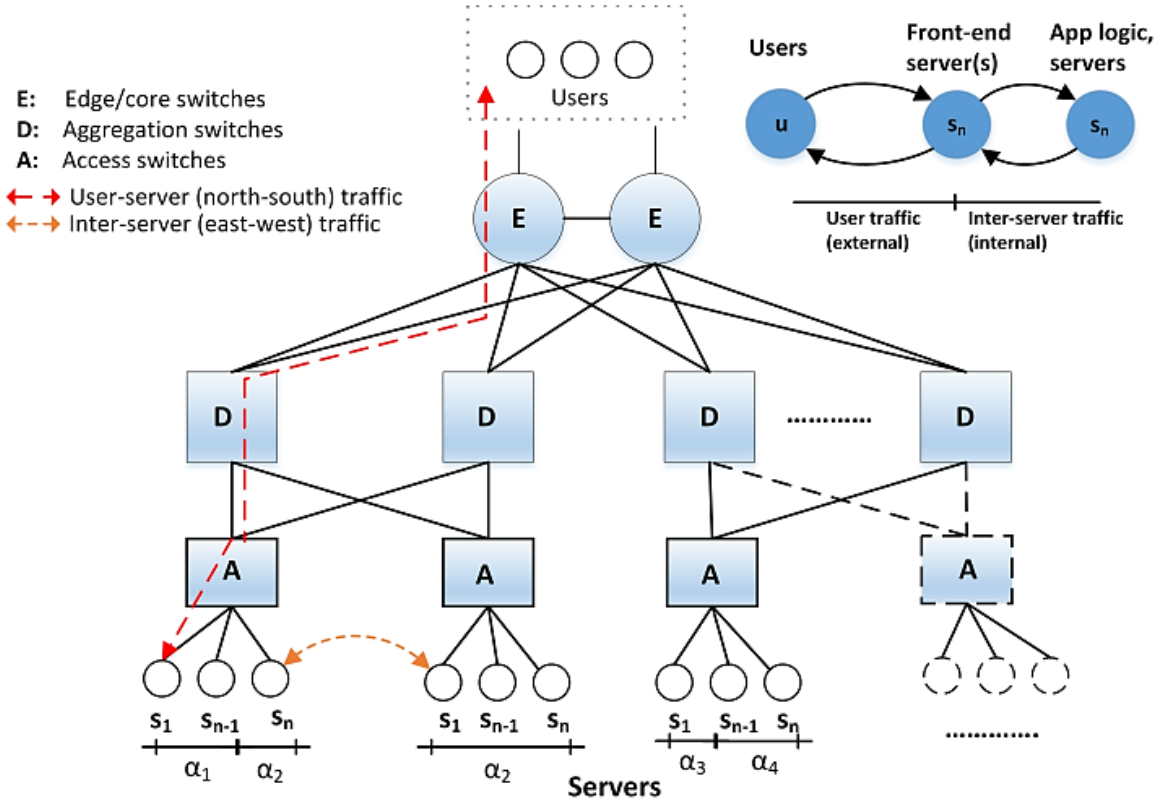


Figure 8.5. Three layer data center topology

8.4.2 External route construction

A three-layer inter-connected network topology prevalent in modern data center architectures to model and evaluate the proposed design is represented in Fig. 8.5. The network provisioning algorithm used for optimizing external user flows is given in Fig. 8.6. The algorithm computes the

inbound and outbound forwarding links per profile for each front-end application server before moving to the next, in order of profile and application hierarchy. A link threshold l_T gives the maximum available β_{max} bandwidth per link. If l_T is greater than the required inbound or outbound flow rate for *u* profile users (l_T > u.z), the link is selected for forwarding. Otherwise users are split between alternate routes with flows equating l_T/z using the selected link and the rest (u=u- l_T/z) split over alternate links as computed during the subsequent iteration. The available bandwidth per link is correspondingly updated ($\beta l_{(E,D)||(D,A)} = \beta l_{(E,D)||(D,A)} - u.z_{inbound||outbound}$). The resulting flow configurations are pushed via OpenFlow *flow_mod* messages to switches using the SDN controller [1][17]. The same process is repeated as long as there exists at least one link between two nodes with l_T > 0, and for instances where all links are at full capacity, the respective flows are forwarded via the last installed route, i.e. link used by preceding application/profile. The algorithm ensures that higher priority profiles continue to experience higher throughput in the event of network congestion by routing lower priority profile flows over links with relatively higher congestion. Conventional load balancing schemes over multi paths (ECMP, DLMBP, etc.) split traffic flows at frame level and each path having a different delay causes out-of-order frame delivery. This results in TCP interpreting these reordered frames as a sign of congestion which ultimately results in degraded performance [294][295]. Our proposed approach ensures that all frames per flow (for each user) are forwarded over the same links to preserve ordered delivery and any splitting of user traffic only occurs at the flow level.

8.4.3 Internal route construction

Similar to external traffic the proposed internal route construction algorithm given in Fig. 8.6 uses the available bandwidth β per link to optimize internal traffic between constituent application servers. Application servers residing on adjoining pods are linked by same set of aggregation switches (D) requiring route computation over links $l_{(A,D)}$, while communication between servers on disjoint pods also requires route computations for flows traversing the core switches i.e. over links $l_{(D,E)}$. The derived application hierarchy table utilizing the profile priority and respective application weightage given in Fig. 8.4 determines the application precedence in assigning forwarding paths between servers. Applications having greater weightage in higher priority profiles therefore, get preference in using forwarding paths experiencing higher throughput and lesser congestion. The maximum available bandwidth β_{max} over each link is given by the respective link threshold l_T. If the pre-set internal flow rate threshold $z_{internal}$ per application for *u* users is greater than the link threshold l_T, the route is selected for flow forwarding. If however, l_T < u.$z_{internal}$, then l_T/$z_{internal}$ flows are forwarded through the link with the remaining flows split over alternate links determined by

the iteration. The process continues for each application as long as there exist one route with l_T >0 between the respective switch pairs, otherwise the last installed route (link) is used for forwarding traffic. The scheduling frequency of this route construction scheme to minimize the computational and controller management overhead is presented in the next sub-section. Furthermore, since the respective traffic management algorithms work in online mode, the time complexity for implementation in realistic scenarios is considered during evaluations.

8.4.4 OpenFlow route installation scheme

To effectively split traffic according to the calculated flow forwarding constructs, network address translation (NAT) is used to place users into segregated subnets each identified with a VLAN ID. In view of limited switch memories (TCAM) [296][297], the scheme also results in minimizing the OpenFlow table sizes despite substantial per profile user connections. An example schematic representing OpenFlow pipeline processing of network traffic towards application server through individual switches is depicted in Fig. 8.7. Table 0 in S1 (edge/core switch) translates and sets NAT IP addresses to profile users and forwards processing to table 1. Flow table 1 assigns a VLAN ID per subnet and the output port for outbound flows. Identification of per-profile flow traffic (as well as distributed traffic from same profile) towards the application server can, in turn, be identified only by the destination address and the VLAN ID to select subsequent outgoing ports in each intermediate switch along the path. As seen in flow table 0 of switches S2 and S3, outgoing traffic is now referred to by the destination server and VLAN IDs to select the outgoing port, substantially reducing the forwarding tables for external flows. Internally within the DC, internal server traffic, the respective server MAC addresses are used for traffic forwarding in respective switch tables to further reduce latency and achieve traffic transfer close to line rate. Inter-server traffic for same application or service in the implemented prototype during evaluation (section 8.6) is therefore, split at the individual server level over multiple links using per server MAC addresses.

start function path_selection (external)

```
for (profile priority P=1, P<=n; P++)
  for (application priority α=1; α <= n; α++)
    #Path selection inbound & outbound traffic, *=last used link
    do
      for ∀ l(E,D)||(D,A)
        l_T (E,D)||(D,A)* = β l(E,D)||(D,A)*
        u_max(E,D)||(D,A) ← l_T / z inbound||outbound
        if u_max(E,D)||(D,A) ≥ u && l_T >0
          flow_mod [l(E,D) , l(D,A)];
          βl(E,D)|| (D,A) = βl(E,D)|| (D,A) – u . z inbound||outbound;
        end if
        else if u_max(E,D)||(D,A) < u && l_T >0
          flow_mod (l(E,D), l(D,A))max_users;
          βl(E,D)|| (D,A) = βl(E,D)|| (D,A) – u . z inbound||outbound;
          u = u – u_max;
        end else
        else if l_T <0
          flow_mod (l(E,D)*||l(D,A)*);
        end else
      end for
    while u> 1;
  end for
end for
```

end function

start function path_selection (internal)

```
for (application priority α=1; α <= n; α++)
  #Path selection internal server-server traffic, *=last used link
  do
    for ∀ l(A,D)||(D,E)
      l_T (A,D)||(D,E)* = βl(A,D)||(D,E)*
      flow_max = βl(A,D) || βl(D,E)
      if l_T(A,D)||(D,E) ≥ z_internal . u && l_T >0
        flow_mod [l(A,D) , l(D,E)];
        βl(A,D) ||(D,E) = βl(A,D) ||(D,E) - z_internal . u;
      end if
      else if l_T(A,D)||(D,E) < z internal . u && l_T >0
        flow_max = βl(A,D)max || βl(D,E)max / z_internal;
        flow_mod [l_T(A,D) , l_T(D,E)];
        u = u - flow_max . z;
        βl(A,D) ||(D,A) = βl(A,D) ||(D,E) - z_internal . u;
      end else
      else if l_T <0
        flow_mod (l(E,D)*||l(D,E)*);
      end else
    end for
  while u>1;
end for
```

end function

Figure 8.6. External (external) route construction algorithm Internal (internal) route construction

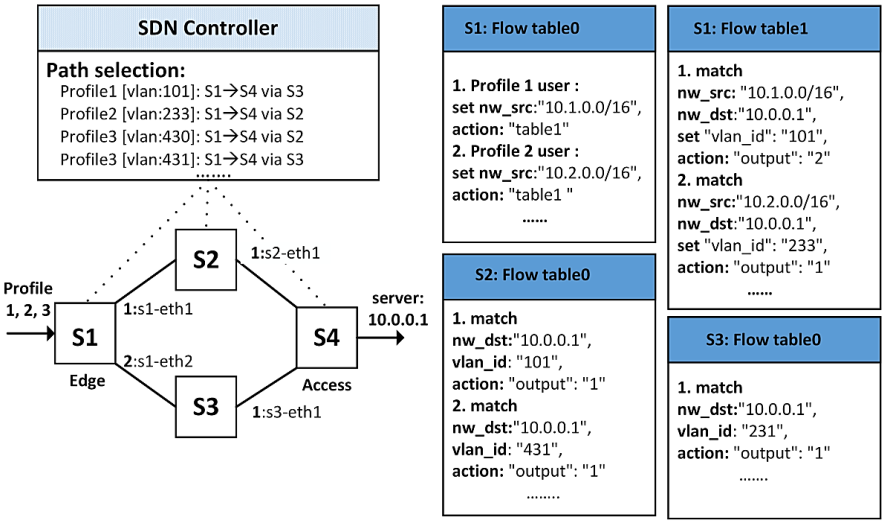


Figure 8.7. OpenFlow pipeline processing –flow installation and route implementation in switches

8.4.5 Real-time route scheduling frequency

Each installed route, by default can accommodate additional users dictated by flow inter-arrival times Δt on each selected path. The external flow construction algorithm in Fig. 8.6 installs flows per link utilizing $z_{in||out}$ flow rates, however, flow inter-arrival time of $\Delta t_{in||out}$ allows the selected link to accommodate users equalling $u_{(ED||DA)}$ given by Eq. 8.3. Similarly, for inter-server routes with flow inter-arrival time threshold $\Delta t_{internal,}$ the selected link is capable of handling flows $flow_{(AD||DE)}$ given by Eq. 8.4.

$$u_{(ED||DA)} = u_{max} / (1- \Delta t_{in||out}) \tag{8.3}$$

$$flow_{(AD||DE)} = flow_{max} / (1- \Delta t_{internal}) \tag{8.4}$$

High inter-arrival times, therefore, translate into a higher tolerance of the installed flows to user connection updates requiring less frequent re-evaluation. The SDN controller monitors real-time user via edge/core switch port monitoring using an average flow threshold to track new/existing and stale user connections. The controller periodically re-computes external and internal forwarding over a link following additional user connections when u(ED||DA) > umax or flow(AD||DE) > flowmax, and immediately on disconnections. Furthermore, re-evaluation of prior installed routes only requires the forwarding routes of the respective profile (with user update) and any subsequent routes in lower priority profiles to be updated. As depicted in Fig. 8.8, addition or deletion of active users in profile k will result in re-computation and assignment of queues in profiles k, l and m and associated inter-server links, leaving pre-installed flows of profile j in force. Reducing control plane overhead remains an avenue of increasing research concentration as highlighted in [297], [298] and [65], and the present flow scheduling scheme aims at decreasing the relative management workload of the SDN controller to improve real-time design scalability.

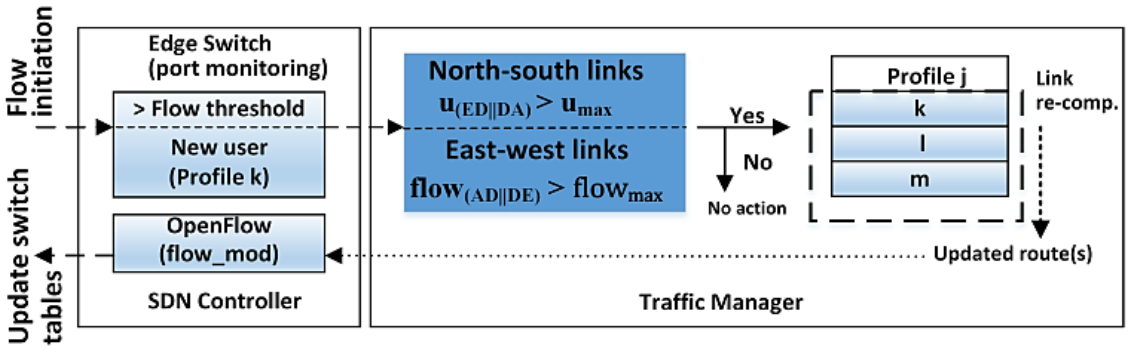


Figure 8.8. Route update scheduling scheme

8.5 Evaluation

To evaluate the effectiveness of proposed traffic management method in an actual network scenario, user traffic profiling was carried out in a realistic campus network segment, part of a larger academic environment. The network comprised of 42 users from computing and engineering departments. Each user had one computer and all user machines in the department connected to local data center servers via the campus network to access hosted applications and services. The user traffic profiles derived from this network segment were used in a simulated data center network using Ryu SDN framework to optimize external traffic between users and the front-end application servers as well as inter-server traffic within the data center. The derived user traffic profiles, data center simulation topology and traffic optimization results are presented in the following sections.

8.5.1 Traffic profile derivation

The profile derivation scheme used NetFlow records exported from the edge of the departmental network, transmitted between user machines and consolidated application servers in the data center over a span of ten weeks from 01/12/2015 to 15/02/2016. A total of approximately 72.2 million flows were examined. To account for replication in nature of user activities, applications were further grouped into distinct categories as depicted in Table 8.2. User traffic was classified by matching user flows against destination IP addresses and ports used by servers and the resulting flows were concatenated every 24 hours [Appendix- 1.2]. The corresponding traffic composition vector depicting application usage distribution as percentage of generated flows for a user u_1 as per Eq. 8.1, for one day of activity (01/12/2015) is given in Eq. 8.5 as follows.

$$u_{1\ [01/12/2015]} = [2.3\ 8.4\ 25.6\ 23.1\ 11.2\ 10.3\ 15.5\ 2.2\ 1.4] \tag{8.5}$$

The resulting traffic composition vectors for all users were subjected to k-means cluster analysis Eq. 3.1 to determine the optimal number of clusters (translating for traffic profiles) appropriately reflecting user activities, the derived clusters were examined starting from k=2, using Everitt and Hothorn technique described earlier. The corresponding plot of 'within groups sum of squares distance' per observation in each cluster against k for present data is given in Fig. 8.9 where a significant drop can be seen up to a cluster size k=6, and minimal subsequent variations up to k=20, indicating an optimal value of 6 profiles for the entire subscriber base. The resulting traffic profiles

Table 8.2. Application Tiers

Application Tier	Applications
Web browsing (w)	Internal and external website
Email (e)	Webmail, Outlook, SMTP, POP3
Storage (g)	Centralized storage, FTP
Streaming (s)	Podcasting, video content
Communication (c)	Office communications server
Enterprise (p)	Corporate information system, staff portal
Publishing (h)	Content management system (document, print)
Software (r)	Software distribution service
Network utility (z)	DNS queries, network multicast

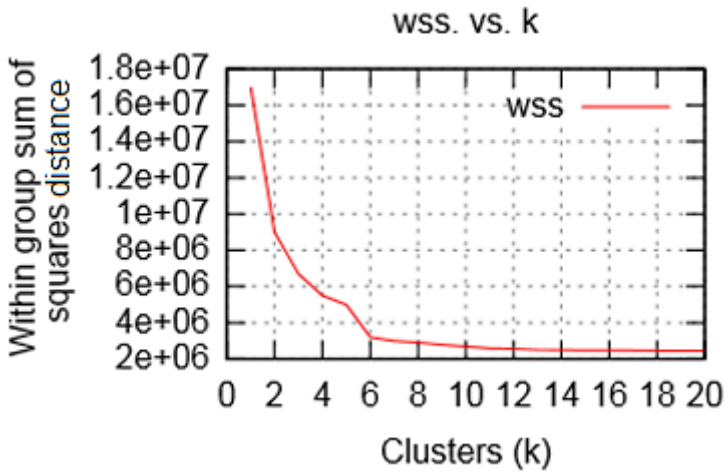


Figure 8.9. Application clusters (k): wss vs. k graph

(k=6), detailing the application trends among user traffic profiles as a percentage of user generated flows are given in Fig. 8.10. Since general network service traffic (z) such as DNS and multicast traffic is not a user-triggered application but a functional one, hence, it was excluded while clustering users and later separately calculated as a percentage of total network flows generated per user profile. From a network management perspective the resulting profiles showed significant variation in user activity. For example, Profile 1 concentrated mainly on web browsing (53.2%) with relatively limited usage of other applications apart from the corporate information and content management services. Profile 2 focused on using communication utilities i.e. the instant messenger and VoIP with limited use of content management applications and minimal use of others. Profile 3 heavily inclined towards corporate information service (65.2%) with significant use of email service

(10.3%) compared to other profiles. Profile 4 heavily tilted towards document and print content creation and using centralized storage facility (11.8). Profile 5 mainly used centralized storage server with small use of content and corporate information server. Profile 6 was a mix of web browsing, emails, storage and corporate applications. Hence, each enterprise user profile represented a significant discrimination towards a certain mix of services. The use of software distribution was, however, significantly low compared to other applications among all user profiles. Fig. 8.11 (a) represents the upload and download rate per profile derived using the probability density function given in Eq. 8.2. The corresponding inter-flow arrival times per profile are given in Fig. 8.11 (b). In view of the discriminative application trends depicted in the derived user profiles and varying flow rates, operators may want control over which users to prioritize in terms of network bandwidth allocation. Furthermore, the stability of the derived profiles over 24 hour time-bins and frequency of outliers in the respective flow statistics may aid administrators in triggering real-time filtering of irregular traffic and minimizing consequences on priority user traffic. Profile stability evaluation and threshold setting to filter out-of-profile flow frequency are discussed in detail in the following section.

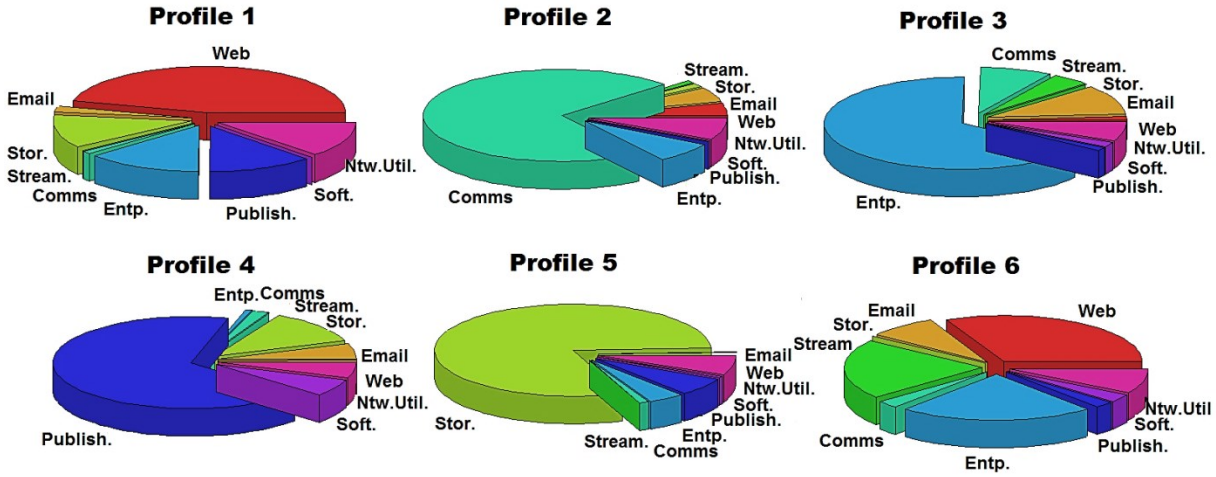


Figure 8.10. User traffic profiles

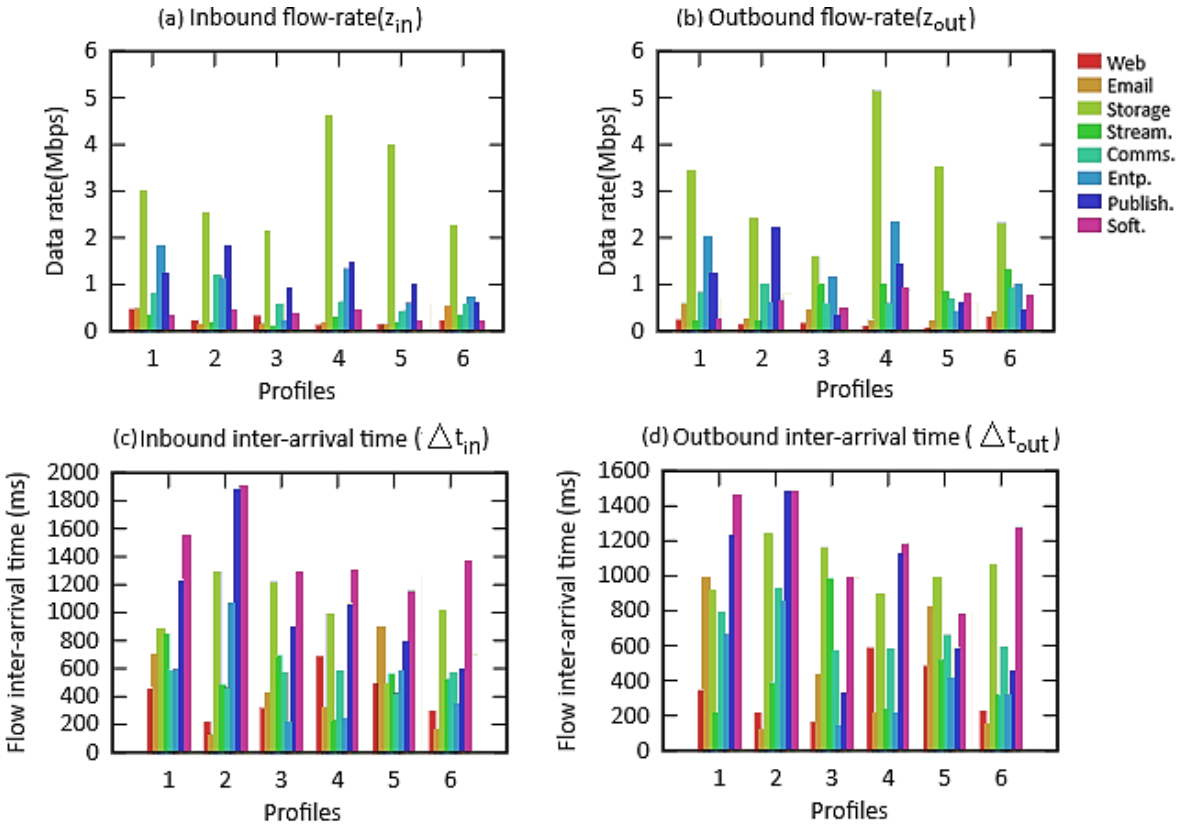


Figure 8.11. Flow rates per profile ($z_{in||out}$) and (b). Flow inter-arrival time per profile ($\Delta t_{in||out}$)

8.5.2 Profile Stability

Profile stability highlights the significance of gaining a better insight to change in user activities and to benchmark the consistency of the extracted profiles and the re-profiling frequency. The average stability of the six profiles derived earlier with respect to application trends over 24 hour time-bins are given in table 3. Profile 5 users showed the highest consistency in retaining profiles at 99.8% followed by profile 4 at 99.4% while profile 6 showed the lowest at 96.9%. The reported profile retention of campus users was greater in comparison with a similar study aimed at evaluating profile stability for multi-device residential users reporting the lowest profile consistency at 81%, undertaken in chapter 4 [293]. Campus users hence, showed a significantly greater degree of consistency in daily application usage in relation to residential users. It was also noted that the minimal irregularity observed was due to inter-profile transitions among users mainly due to proportional variation in the same kind of user activity rather than a complete change of user roles or introduction of new profiles. The consolidated inter-flow arrival times and flow rates per profile are given in Fig. 8.12. As depicted in Table 8.1, from a network management perspective, consolidated per-profile flow statistics aid administrators in setting a threshold to identify real-time anomalous (out-of-profile) traffic for subsequent filtering and for profile regeneration. For example, configuring the traffic manager to monitor real-time flow statistics according to per profile aggregate flow statistics would result in automatically placing flows exceeding the threshold in the guest profile to reduce consequence on priority profile traffic.

Table 8.3. Average probability of profile regularity (/24 hour time-bins)

User Profiles	No Change	Change (Outliers)
Profile 1	0.983	0.017
Profile 2	0.975	0.025
Profile 3	0.987	0.013
Profile 4	0.994	0.006
Profile 5	0.998	0.002
Profile 6	0.969	0.031

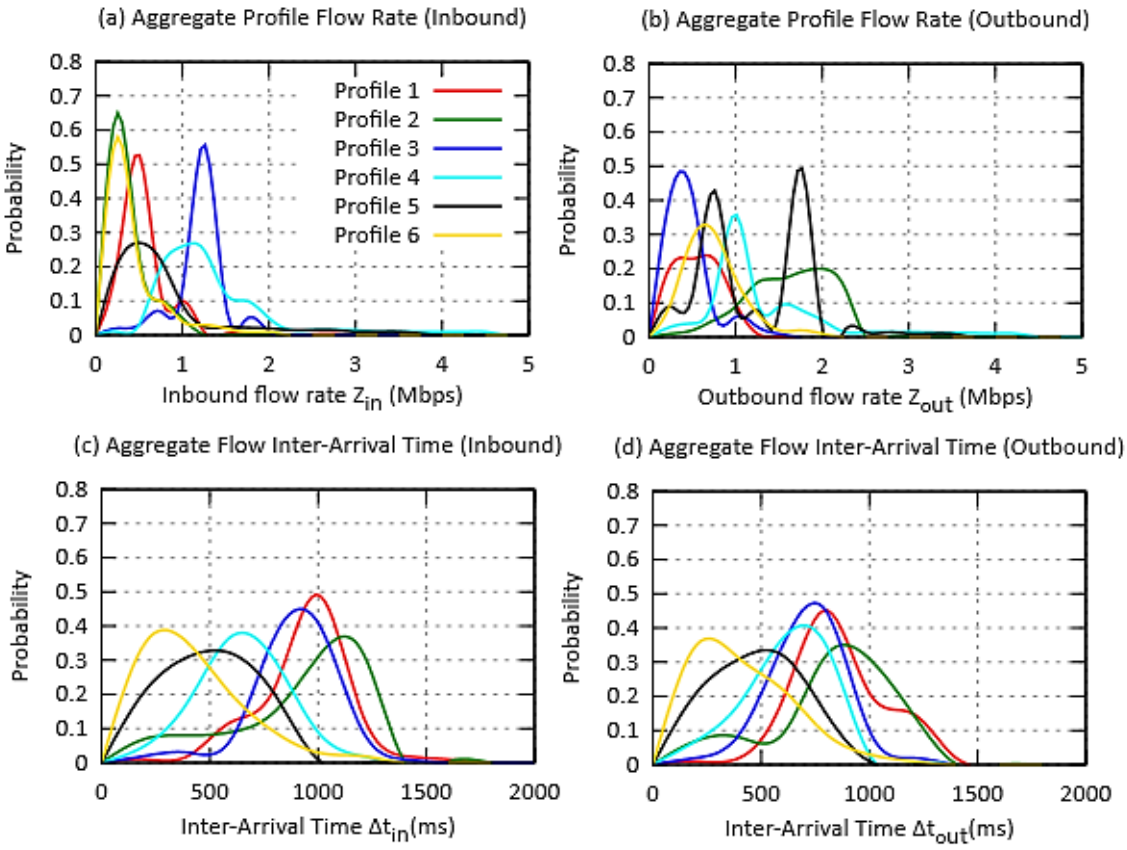


Figure 8.12. Aggregate flow rate and inter-arrival time threshold per profile

8.5.3 Simulation environment

The simulation environment comprised of a DC topology, traffic generation scheme and sample profile and application hierarchy to empirically evaluate the results of the proposed traffic management design. The respective set of parameters and utilities used to this effect are detailed as follows.

- *DC topology:* The proposed design was evaluated using Mininet network emulator [103] utilizing Ryu SDN framework [26] and the derived user traffic profiles simulated in a DC topology comprising a total of eighty servers (ten per pod), ten per application tier as shown in Fig. 8.13. The servers for each application were dispersed between disjoint pods to evaluate the traffic management design under a high inter-server traffic scenario [Appendix – 4.2].

- *Traffic generation:* Ostinato traffic generation utility [205] was used for modelling external and internal flow rates according to the derived statistics as per Fig. 8.11 with an effective flow threshold set to one flow per user in the simulation to identify active users. Given the

enormity of inter-server traffic within the DC compared to external traffic as discussed in [286], [288] and [21], the threshold for internal flow rates between each pair of application servers ($z_{internal}$) was set to randomly transmit at up to four times the external outbound flows rates per-profile given in Fig. 8.11 (a). Correspondingly the flow inter-arrival time ($\Delta t_{internal}$) for internal traffic between servers per application tier depicted in Fig. 8.11 (b) was proportionally reduced to analyse the effects of network congestion on high and low priority profiles with increasing user connections. To account for anomalous (out-of-profile) traffic, percentage of user traffic per profile was varied in accordance with table 3, exceeding the thresholds given in Fig. 12 at each simulated user load.

- *Sample profile and application hierarchy:* A sample profile priority table was used with the corresponding application hierarchy based on application usage weighting starting with highest profile represented in Table 8.4.

- *Traffic management:* Using Table 8.4, along with the current as well as predicted traffic per profile, the SDN traffic manager computed the optimal user to front-end server routes along with the flow forwarding constructs for inter-server traffic. The computed flows were afterwards installed in network switches via the controller using OpenFlow protocol and the iteration continued tracking the number of real-time user connections [Appendix – 5.4].

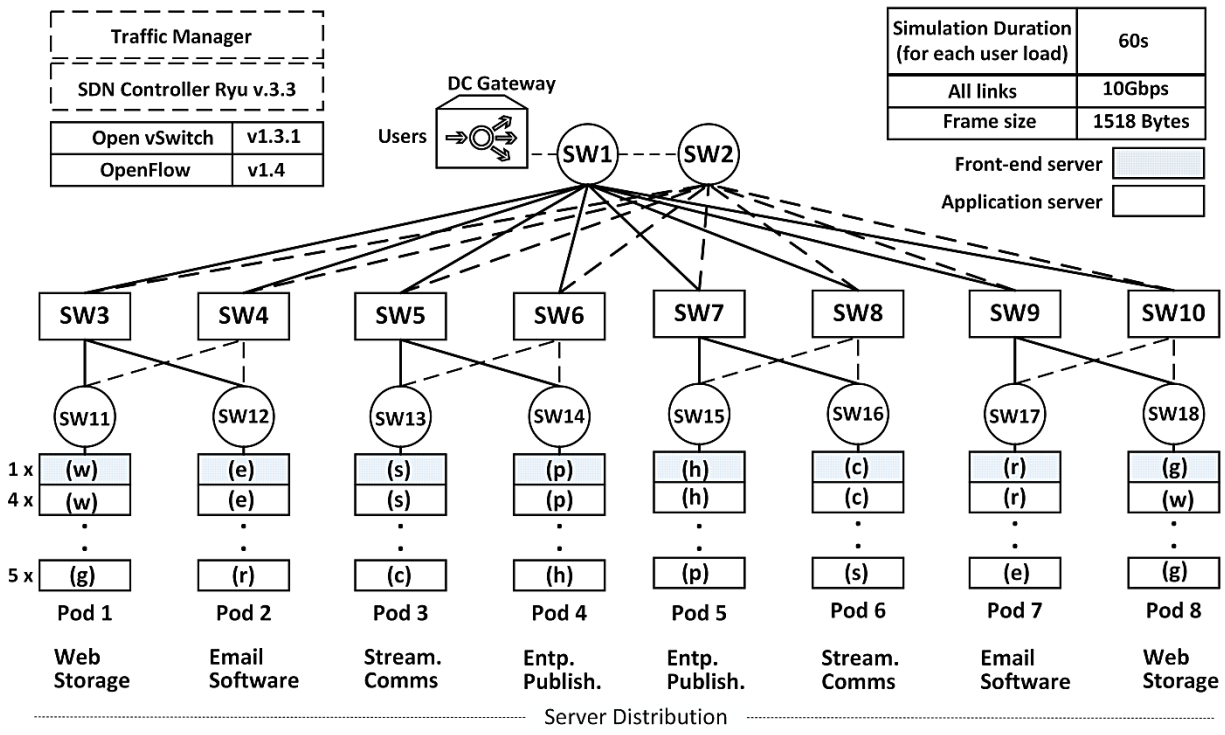


Figure 8.13. Simulated data center environment

Table 8.4. Sample profile priority table

Profile priority	Profiles	Application Hierarchy
1	Profile 3	Enterprise Email Communication Streaming Software Publishing Web-browsing Storage
2	Profile 2	
3	Profile 1	
4	Profile 6	
5	Profile 4	
6	Profile 5	
7	Guest	

8.5.4 Throughput and bandwidth results

The simulation results measured the effectiveness of the proposed profiling based real-time traffic optimization against conventional traffic management schemes i.e. ECMP and STP. Employing ECMP or STP to optimize a specific application in isolation would result in improved performance of the respective application, in relation to other data center hosted services. The present simulation, however, provisioned DC links among all applications equally using the conventional schemes to provide an overall comparison of the results against the proposed profiling mechanism. The simulation therefore, aims to evaluate the benefit of profiling based traffic management over individual application weightage models, regardless of the particular application being optimized by ECMP or STP, using the SDN framework. Furthermore, to monitor the traffic statistics varying user loads, effective throughput between users and front-end servers (SW[1-2], SW[11-18]) as well as between individual application servers (SW[11-18]) residing on disjoint pods was recorded using OpenFlow switch port statistics.

The first test compared STP, ECMP and the proposed profiling-based scheme frame delivery ratio and throughput (total received frames) performance for the external inbound traffic for the top priority profile 3 and lowest priority profile 5, for highest priority application (Enterprise) while increasing user loads across all profiles. The corresponding parameters are given in Tables 8.5-8.8. As shown in Fig. 8.14(a) and (b) profile 3 users consistently experienced high frame delivery and throughput using profiling based optimization compared to the ECMP and STP scheme. STP used a loop free environment limiting utilization of all available links while ECMP equally balanced the traffic across all links. The absence of profiling-based forwarding, resulted in profile 3 users experiencing significantly lower frame delivery (≤ 21%) and throughput (≤ 35%) with increasing user loads (> 300 users per profile) despite being high priority users. Similarly, profiling based traffic optimization of the lowest priority profile 5 resulted in improved frame delivery (~39%) and

throughput (~37%) using the profiling scheme shown in Fig. 8.14(c) and (d). The resulting improvement was due to the higher application priority of the enterprise tier despite sharing links with other lower priority application servers on adjacent pods (i.e. the publishing tier) at increasing user loads (≥ 300 users per profile) As evident from the profile 5 routing paths given in Table 8.7, at very high user loads (≥ 600 users per profile), profiling based optimization ensured profile 5 traffic continued to use the SW1:SW6:SW14 path. The effects of oversubscription were hence, localized on the alternative SW2:SW6:SW14 path, mainly carrying internal inter-server traffic using the profile prioritization scheme.

Table 8.5. Basic Parameters – Profile 3 ←→ Enterprise Front-end

Name	Value
Profile 3 z_{in}	0.214Mbps
Profile 3 z_{out}	1.134Mbps
Profile 3 Δt_{in}	857ms
Profile 3 Δt_{out}	952ms

Table 8.6. Basic Parameters – Profile 5 ←→ Enterprise Front-end

Name	Value
Profile 5 z_{in}	0.581Mbps
Profile 5 z_{out}	0.612Mbps
Profile 5 Δt_{in}	3200ms
Profile 5 Δt_{out}	2400ms

Table 8.7. Profile 5 Routing Path: User → Enterprise Front-end

User load	Inbound Traffic				Scheme	Route
	Pod4 (Gbps)	Pod3+4 (Gbps)	P5 Entp. (Gbps)	Preceding P5, Entp. (Gbps)		
600 users	14.889	38.568	0.348	3.144	Profiling	SW1:SW6:SW14
					ECMP	SW[1-2]:SW[5-6]:SW14
					STP	SW1:SW6:SW14
700 users	17.369	44.996	0.406	3.668	Profiling	SW1:SW6:SW14
					ECMP	SW[1-2]:SW[5-6]:SW14
					STP	SW1:SW6:SW14

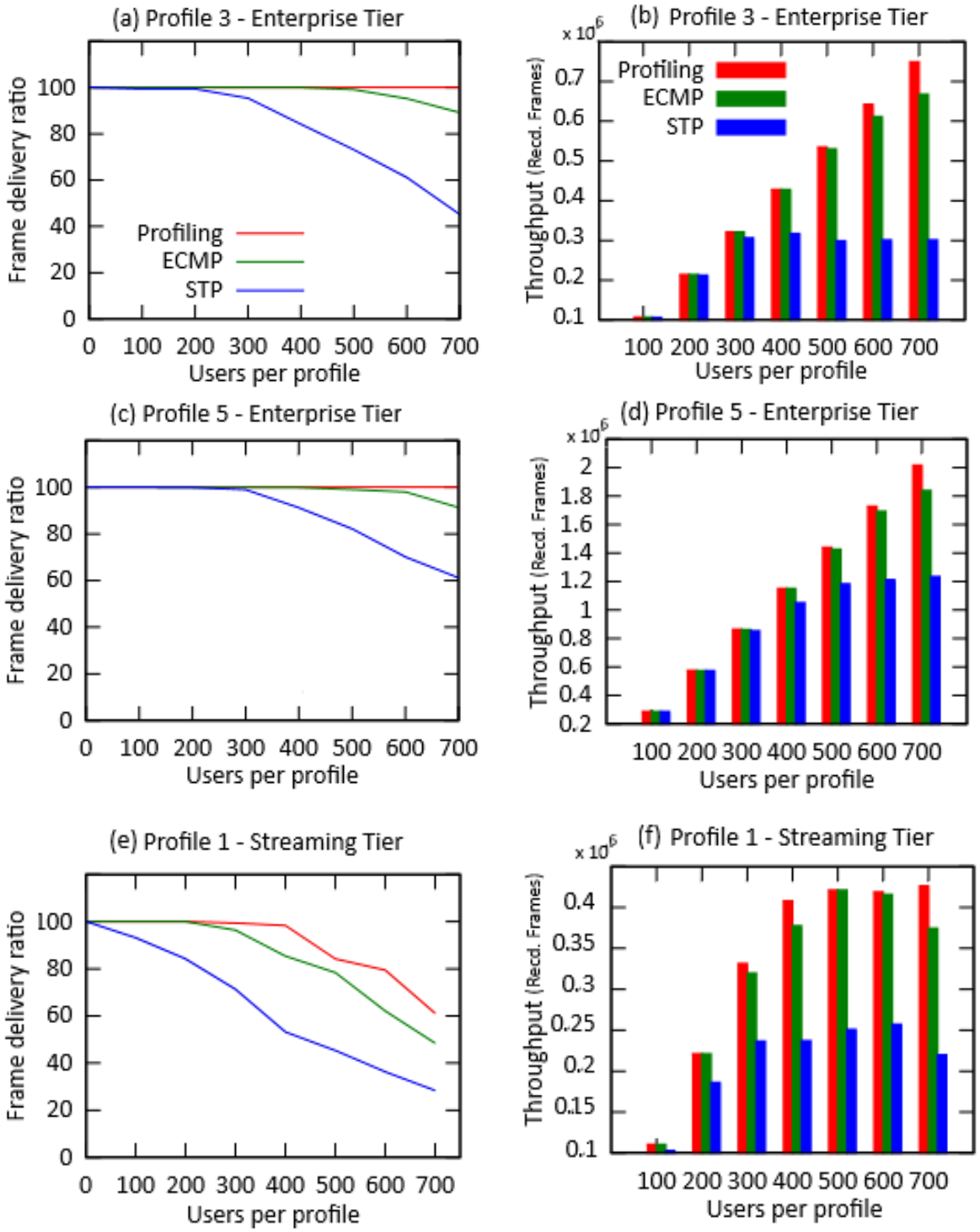


Figure 8.14. Frame delivery ratio and throughput measurement

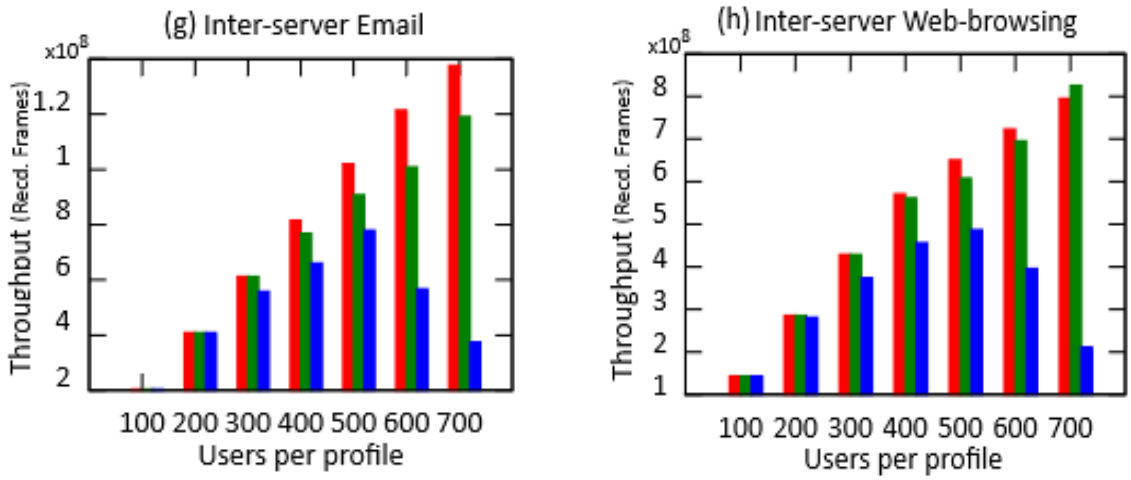


Figure 8.14. Frame delivery ratio and throughput measurement (continued)

Table 8.8. Basic Parameters – Profile 1 ←→ Streaming Front-end

Name	Value
Profile 1 z_{in}	0.212Mbps
Profile 1 z_{out}	2.21Mbps
Profile 1 Δt_{in}	2539ms
Profile 1 Δt_{out}	1454ms

Table 8.9. Profile 1 Routing Path: Streaming Front-end → User

User load	Outbound Traffic				Scheme	Route
	Pod3 (Gbps)	Pod3+4 (Gbps)	P1 Stream (Gbps)	Preceding P1, Stream. (Gbps)		
300 users	20.736	32.142	1.326	5.868	Profiling	SW13:SW5:SW1
					ECMP	SW13:SW[5-6]:SW[1-2]
					STP	SW13:SW5:SW1
500 users	34.561	41.471	2.212	9.181	Profiling	SW13:SW[5-6]:SW1
					ECMP	SW13:SW[5-6]:SW[1-2]
					STP	SW13:SW5:SW1

After analysing the top and bottom priority profile external traffic performance, in the second test, frame delivery ratio and throughput were measured for medium priority profile 1 users from the front-end server to the user i.e. outbound traffic. The performance was measured for the lowest used profile 1 application i.e. streaming, also having medium application priority. The corresponding traffic parameters are given in Tables 8.8-8.9. The relevant frame delivery and

throughput statistics are given in Fig. 8.14 (e) and (f) respectively. It was observed that the that profiling-based optimization significantly outperformed ECMP and STP (≥ 300 users per profile) due to ECMP load-balancing traffic over all links as shown in routing paths depicted in Table 8.8 while profiling scheme routing profile 1 traffic over the first path [SW13:SW5:SW1] and forwarding the subsequent lower priority traffic over alternate links. For 300 users per profile, the total traffic out of pod 3was 20.736Gbps, the external priority traffic preceding profile 1 streaming users around 5.868Gbps and profile 1 streaming users at 1.326Gbps. The two outbound links (20Gbps) from the access switch SW13, the first link [SW13:SW5:SW1] therefore, carried outbound profile 1 streaming traffic without penalty. ECMP in comparison load-balanced traffic over all paths resulting in decreased frame delivery ratio (98.16%) and throughput (0.314 million frames). The trend scaled well up to 500 users, where traffic out of pod 3 increased to 34.561Gbps with profile 1 streaming traffic accounting for approximately 2.21Gbps and the priority traffic preceding profile 1 being around 9.18Gbps. Hence, of two links out of pod 4, profile 1 traffic was split over first link (0.82Gbps) and second link (0.39Gbps). Since the second path [SW13:SW6:SW1], also carried inter-server traffic and was oversubscribed, the frame delivery ratio using profiling management, dropped to approximately, 81.34%. The trend continued further, with increasing user connections (in higher priority profiles), and users in profile 1 pushed to the second link, closing the gap between ECMP and profiling based optimization up to 700 users per profile. Hence, even for medium priority profile and mid-tier application, the performance throughput was considerably better even with substantially high user loads when compared with conventional load-balancing techniques.

To evaluate inter-server traffic performance between same application servers residing on disjoint pods, throughput for the Email tier closer to the top of the global application hierarchy table and web-browsing towards the bottom was tested and is given in Fig.8.14 (g) and (h). The corresponding traffic parameters are given in Tables 8.10-8.11. For the Email tier, the throughput was measured between switches SW12 and SW17 (pods 2 and 7) and for web browsing servers between SW11 and SW18 (pods 1 and 8), owing the location of the respective servers. Profiling optimization gave improved overall throughput between pods 2 and 7 for Email traffic even at maximum user load of 700 per profile, owing higher priority among other applications traversing the same links i.e. web-browsing, software and storage tiers via the aggregate and core switches. At a load of approximately 600 users per profile, the external outbound traffic preceding inter-pod Email traffic forced Email traffic to split over two paths SW17:SW9 the primary and SW17:SW10 the alternative with the later carrying remaining application traffic from software tier. As observed

Table 8.10. Basic Parameters – Inter-server Traffic

Name	Value
Inter-server Email traffic (e) $z_{internal}$	1.528– 6.112Mbps
Email (e) $\Delta t_{internal}$	0 - 125ms
Inter-server Browsing traffic (w) $z_{internal}$	1.134 – 4.536Mbps
Browsing (w) $\Delta t_{internal}$	0 - 625ms

Table 8.11. Routing Path: Web browsing [Pod8:Pod1]

User load	Outbound Traffic			Scheme	Route
	Pod8 (Gbps)	Browsing (Gbps)	Preceding Browsing (Gbps)		
400 users	23.218	1.143	7.332	Profiling	SW18:SW10:SW1:SW3
				ECMP	SW18:SW[9-10]:SW[1-2]:SW3
				STP	SW18:SW10:SW1:SW3
500 users	29.023	1.429	9.165	Profiling	SW18:SW9:SW1:SW3 SW18:SW10:SW1:SW3
				ECMP	SW18:SW[9-10]:SW[1-2]:SW3
				STP	SW18:SW10:SW1:SW3

during external traffic management, any increase in preceding (priority) traffic, low priority application traffic may fully shift to secondary links that may be oversubscribed without substantial consequence for high priority Email tier. For web-browsing server tier, both profiling and ECMP based traffic management perform equally up until the maximum user load of 700 users per profile. For 400 users per profile, browsing server traffic from pod 8 to pod2 was around 1.143Gbps carried over path SW18:SW10, preceding priority traffic out of pod8 being 7.332Gbps out of pod8 and remaining inter-server traffic (mainly storage tier) approximating 14.743Gbps was split over both SW18:SW10 and SW18:SW9 paths. Since the total outward traffic exceeded the combined link capacity (20Gbps), uniform load balancing across all links using ECMP resulted in lower throughput performance for browsing than the devised profiling based management scheme.

At 500 user load of users per profile, external pod8 traffic having higher priority than browsing traffic approximated at 9.165Gbps. The web browsing server traffic reaching 1.429Gbps, was, split into using the SW18:SW10 path (0.715Gbps) with remaining (0.714Gbps) routed over the oversubscribed SW18:SW9 path carrying approximately 19Gbps traffic. The trend continued with further increase in preceding traffic resulting in web-tier shifting to oversubscribed links resulting in

a marginal decrease in throughput compared to ECMP at 700 user connections per profile. Profiling based throughput reduced below ECMP as with the latter browsing traffic was still being load balanced using all links, however profiling scheme forced inter-server browsing traffic on the last oversubscribed link.

As evident from the above examples, profiling based traffic management forwards priority traffic over links with higher available bandwidth forcing succeeding profiles and applications on tertiary links reducing the effects of network congestion on high priority traffic due to oversubscription. However, the effectiveness of the proposed traffic forwarding design, relies on relieving adverse network performance due to link oversubscription at the expense of low priority users and (or) applications. In comparison, weighted bandwidth sharing models utilizing technologies such as ECMP, or conventional schemes like STP fall short of delivering for high priority users, and at best allow network fabric provisioning uniformly or only at the application level. The proposed user traffic profiling integration methodology in the traffic optimization framework accounts for the mix of application trends making user-defined traffic optimization possible. The next section examines the frequency of flow updating schedule as well as the management overhead associated with the simulated DC traffic optimization.

8.5.5 Flow management overhead

The effects of profiling based route installation and the flow update scheduling frequency are empirically evaluated at the simulated user loads to evaluate the scalability of the proposed approach. The present simulation therefore, monitored (i) the average number of flow entries at switch level using the VLAN tagged routes discussed in section 8.4.4 as well as (ii) the reduction in real-time flow updating frequency employing the per profile flow inter-arrival duration and flow rate computations highlighted in section 8.4.5. The respective numbers of flow entries were monitored using *table_stat* while the percentage of flows updated were observed at each user load simulation (duration: 60s) using *flow_stat* OpenFlow messages. The cumulative distribution of total flow entries per switch employing the profile route installation *(ri)* schema as well as the expected number of entries without the proposed approach at varying user loads are presented in Fig.8.15(a). Using profile based route installation (VLANs) the average number of entries at each switch level is only fractional compared to the substantial flow table sizes required otherwise. As mentioned earlier, a large number of flow entries in switches present a challenge given the limited memory available in OpenFlow compliant devices [26][27]. The major proportion of flows (80%) per switch using VLAN route installation remains within 100 table entries despite the simulated users loads of

up to 700 users per profile. The core switches comprise of smallest forwarding table sizes with maximum of 97 entries (excluding the NAT functionality) compared to access and distribution table sizes recording a maximum of 106 and 119 entries per switch respectively. The expected flow table sizes without profiling route installation scheme, however, are considerably larger with maximum core switch table size of around 2320 entries per switch and distribution and access switches going beyond 250 entries per switch. The potential reduction in table sizes using the route installation scheme therefore, presents a saving of approximately 23% - 95% entries in the DC switches at simulated user loads. Since, most SDN compatible hardware the flow tables need to be implemented in TCAM, relatively expensive and larger than standard memory (RAM) and therefore, reducing the average flow entries per switch scales well in SDN based DC.

The cumulative distribution of the total flow updates to varying user load ratio, using the route scheduling *(rs)* scheme is given in Fig. 8.15(b). The flow update frequency at the core switch level was lowest followed by access and the distribution switches. Minimum updating at the core level was due to the minimum and less frequent changes required in the core switches with variation in user loads. The management overhead saving of the route scheduling *(rs)* scheme utilizing flow rate and inter-arrival interval computations to accommodate a greater number of users on installed routes and thereby reduce flow modifications was substantial. The frequent updating of installed flows via the SDN controller increases the OpenFlow control channel overhead (traffic) increasing latency involved in implementing updated rules and subsequently affecting real-time traffic forwarding [297-298][65]. The potential decrease in overhead ranged between 18% - 31% using intelligent route scheduling compared to the lack of an efficient updating scheme. Furthermore, to visualize the result of the flow scheduling on profile traffic, three profiles and three application tiers were selected from the top, medium and bottom of the respective hierarchies, depicted in Fig. 8.15 (c) and (d). The medium priority profile6 showed maximum flow update frequency followed by core and guest profiles. For the highest priority profile3 the saving in flow updates due to route scheduling ranged between 49% - 64%. Guest profile accounting for out-of-profile traffic showed the lowest flow updates mainly attributed to the minimum total flow installations catering anomalous traffic. Among the applications, total potential savings in route updates due to the route scheduling scheme ranged between 39% - 55% at varying user loads, the highest reduction recorded for the highest priority communications tier. Profiles and applications higher up the priority table therefore, showed a lower flow update frequency compared to lower priority traffic as due to route scheduling scheme, the former remain relatively unaffected by updates further

down the hierarchy. The latency and controller overhead reduction achieved due to profiling based route scheduling are considered in the following subsections.

8.5.6 Time complexity analysis

Further to improvements in the management overhead using reduced tables and scheduling it is also important to evaluate the time complexity benefit of the approach. The average latency involved in computing routes and completing flow installations in individual switches was therefore, calibrated and illustrated in Fig. 8.15(e). The analysis considered the total duration of OpenFlow *flow_mod* message generation via the controller and respective flow activation in the switch. To measure the processing of *flow_mod* messages, an OpenFlow *barrier_request* was sent after sending all *flow_mod* messages per switch [Appendix – 5.4]. The OpenFlow *barrier_request* message ensures that the switch completes processing of all sent messages before issuing a *barrier_reply*, indicating the *flow-mod* message has been fully processed at the switch. The results show that minimal flow update frequency employed by the route scheduling scheme *(rs)* translates into comparatively lower latency in creating flow constructs in switches. The highest average latency was observed in updating access switch routes approximating at 2248ms. Access switches serve both internal and external traffic and therefore, the average computational and processing latency attributed to the lowest level in the switch hierarchy was greater than the aggregate and core level. The average maximum recorded per core and distribution switch approximated at 2120ms and 1998ms respectively. The overall reduction in latency due to route scheduling ranged between 23% - 41% (135ms-725ms) per switch level at varying user loads. The route computation and installation duration comprised 0.67% - 3.6% of the total simulation duration (60s) per user load across the entire DC switching fabric. The route scheduling scheme therefore, showed considerably reduced dynamic route construction latency following profile membership updates.

In addition to the flow update latency involved at switch level, the time complexity involved in detecting and re-routing of the simulated anomalous traffic is also considered. The latency measurement comprises of the traffic monitor detecting the anticipated profile flow threshold violation(s) followed by *flow_mod* message processing to route traffic under the lowest priority guest profile. As depicted in Fig. 8.15(f), the detection latency remained largely within 1000ms and the installation (or updating) of flows ranged between 1185ms - 1400ms. The total timespan of detection and re-routing of anomalous flows under lowest guest priority therefore, averaged at approximately 2293ms, or 3.8% per simulation duration at varying loads. From a real-time traffic management perspective, the recorded latency presents swift real-time re-routing of out-of-profile

traffic minimizing the adverse consequences on remaining flows, until the network manager can examine the anomalies; possibly re-evaluate the user profiles or the existing profile prioritization.

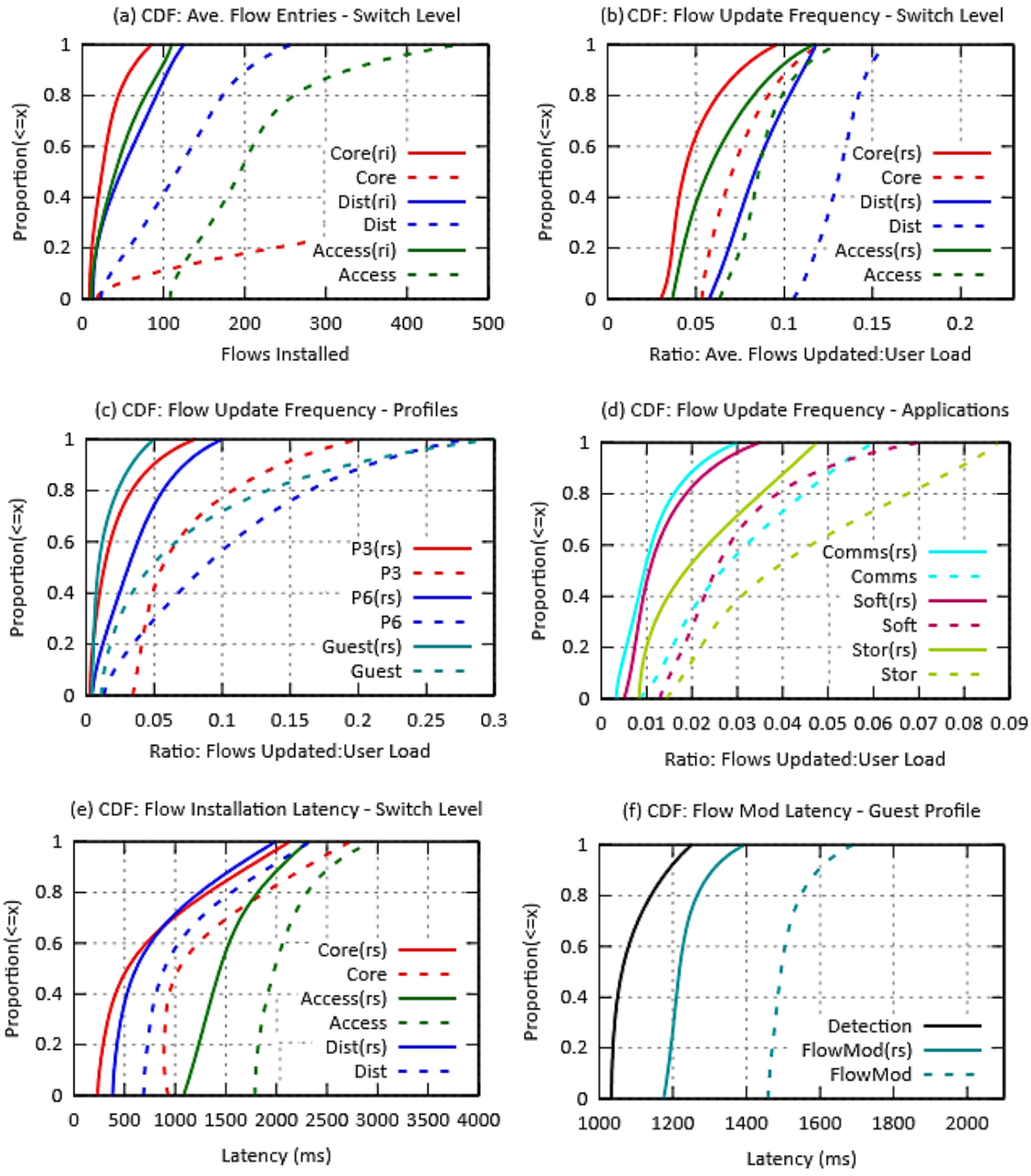


Figure 8.15. Flow statistics and latency measurement

8.5.7 OpenFlow control traffic

The average OpenFlow control channel traffic generated between the controller and DC switches as a result of OpenFlow monitoring and flow installation/update messages is measured at each simulated user load and illustrated in Fig. 8.16. Using the route scheduling scheme, the maximum upstream and downstream traffic recorded at the core switch ranged at 187kbps and 789kbps respectively. Higher core switch control traffic using route scheduling at core switches was due to the VLAN addressing functionality generating a significantly greater amount of *flow_mod* messages downstream and corresponding *flow_stat* and *table_stat* message replies upstream tracking the increase in profile memberships. The distribution control traffic recorded a maximum of 87kbps upstream and 412kbps downstream. The average access switch control traffic, however, remained comparatively low with the uplink maximum at 67kbps and downlink at 235kbps despite the greater share of total inter-server traffic routes carried by access switches. Lower average control traffic overhead per access switch was attributed to uneven distribution of the total access switch control traffic, with few switches having bulk of the control traffic share in relation to a more uniform division at aggregation points higher up the DC switch hierarchy. At each level of switch hierarchy except the core the total upstream and downstream traffic remained significantly lower employing the profile route scheduling. The average reduction in control traffic across access and distribution DC switches due to profile route scheduling switches ranged between 7-16% on the upstream and 21%-46% on the downlink respectively. To further streamline and balance the control traffic, operators may utilize several controllers each catering to particular switch subset(s) for improved redundancy. However, the placement of the controllers as well as the employability of in-band or an external overlay for carrying the OpenFlow controller-switch traffic would greatly depend on the DC topology and the prevailing traffic conditions. In the present scenario, however, decreased flow update frequency resulted in significant reduction in the control overhead at the distribution and access levels while using a single controller.

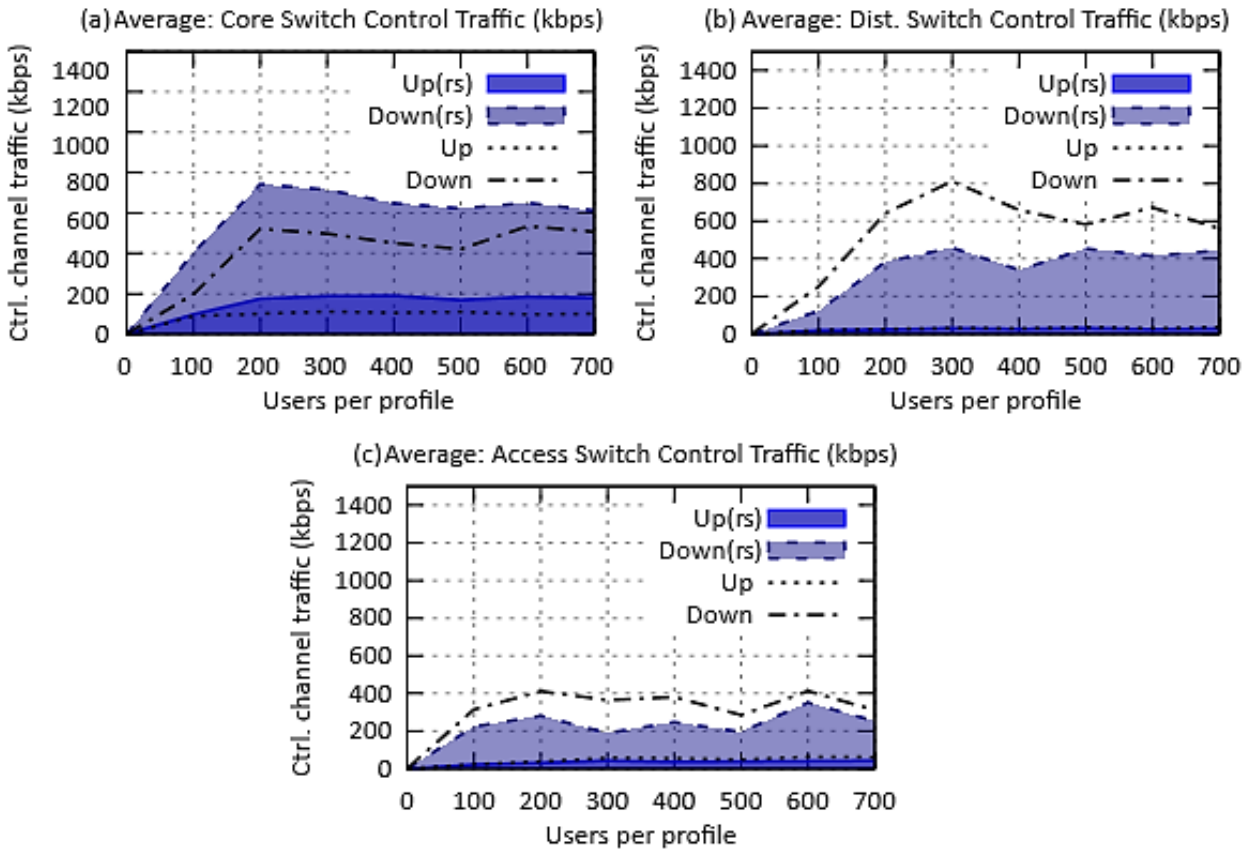


Figure 8.16. Average OpenFlow control channel traffic (kbps)

8.6 Conclusion

The enterprise network used in the study comprised of diverse application trends with varying traffic statistics per profile. Implementing isolated application performance in consolidated DC utilizing conventional load-balancing methods for the extracted user profiles would lead to degraded performance for users requiring optimal forwarding. The benefits of profiling based resource provisioning are of particular significance at higher user loads, where high priority profiles experience improved throughput and frame delivery ratio compared to the conventional load-balancing techniques. It is however, noticeable that due to greater link oversubscription at higher loads only a subset of profiles and applications may be allocated optimal paths for both external and internal DC traffic, the selection depending on administrator-assigned priority to user profiles and the subsequently derived application hierarchy. Using SDN based traffic engineering allows the dynamic implementation of constructed routes with changing user connections, a significant improvement over present manually intensive network provisioning techniques. Furthermore, the relatively lower flow update scheduling frequency and subsequent reduced overhead of control traffic inherent in the design offers high scalability for real-time implementation.

To conclude the work of this thesis, the following chapter provides a summarization of the research project including key achievements, limitations and scope for future work in the SDN traffic engineering domain.

Chapter 9 Conclusions and Future Work

The present chapter summaries the thesis by reviewing the main achievements of this research and discussing its limitations. The chapter also highlights future research directions within user-centric traffic engineering solutions in software defined networking.

9.1 Achievements of the research

Overall, the project has achieved all the objectives initially set out in **chapter 1**, with a series of investigations and experimental simulations undertaken towards the development of a user traffic profiling mechanism to be used in the SDN framework. The full achievements are listed as follows.

1. An experimental investigation of the feasibility of user traffic profiling through flow-based measurements (**chapter 3 and chapter 4**). An experimental study was conducted on real user application usage from a residential building housing around 250 users. Firstly, by utilising the k-means clustering algorithm, traffic profiles were derived based on user generated traffic over a one-month time frame. The resulting profiles presented significant discrimination in user activity, from a network management perspective. The profile derivation method was further compared to other popular clustering algorithms (hierarchical clustering and DBSCAN) and the stability of profiles was benchmarked to ascertain their suitability for integration in a real-time SDN traffic management solution (**chapter 4**). Since each residential user premises during the study consisted of multiple devices (mobiles, laptops, etc.), the work also evaluated the inter-profile migration for each user device. The extracted traffic profiles per user premises show a great deal of stability over the examined 24-hour time-bins, showing a probability of profile change varying between 3-19%. Any inter-profile transition for a specific user device is mainly attributed to proportional variation in the same activity rather than a complete change of roles. This high level of profile stability, even in a multi-device user environment, successfully demonstrates the potential of user traffic profiling based controls for creating user-centric network policy primitives in SDN.

2. The design and evaluation of a novel traffic engineering framework integrating user traffic profiling controls in residential SDN (**chapter 5**). Software defined networking (SDN) provides a centralized control framework with real-time control of network components

including residential customer routers to allow automated per-user bandwidth allocation. However, employing dynamic traffic shaping for efficient bandwidth utilization among residential users is a challenging task. In this context, user traffic profiling was employed in residential networking to understand application usage requirements for each individual user and translating them into network policies. The proposal is implemented using the previously derived user traffic profiles (**chapter 4)** and an SDN traffic monitoring and management application is designed for implementing hierarchical token bucket (HTB) queues customized for individual user profiles in real-time, according to user-defined profile priorities. The traffic management scheme scales well under both upstream and downstream network congestion simulations by dynamically allocating dedicated bandwidth to users based on their profile priority, resulting in a decreased packet loss and latency for a selected set of high priority users. Compared to previously proposed approaches of integrating SDN controllers on the service provider side driving millions of residential gateways, the use of a local profiling engine and SDN controller incorporated in the residential network offers greater design scalability. The proposed framework can also easily provide additional controls, such as temporal profile prioritization and data usage allocations per profile, allowing residential users more control over their network usage.

3. The investigation and design of a machine learning based traffic flow classifier for use in real-time application identification and subsequent profiling in practical settings (**chapter 6**). IP address and port based traffic classification although scalable and computationally efficient remains far from an ideal solution, especially in environments where users are frequenting a range of Internet services as opposed to locally hosted data sources (servers). Despite widespread use, flow accounting methods are considered inadequate for classification purposes or require additional packet and host behaviour information limiting their practical adoption. To overcome these challenges, a per-flow classification mechanism was proposed using a two-phased machine learning approach incorporating k-means and C5.0 algorithms, with flow records (NetFlow) as input. The individual flow classes were derived per-application through k-means and then further used to train a C5.0 decision tree classifier. As part of validation, the initial unsupervised phase used flow records of fifteen popular Internet applications collected and independently subjected to k-means clustering to determine unique flow classes generated per application. The derived flow classes were then used to train and test a supervised C5.0 based decision tree. The resulting classifier presented an average accuracy of 92.37% on approximately 3.4 million test cases,

increasing to 96.67% with adaptive boosting. The classifier specificity factor, which accounts for differentiating content-specific from supplementary flows ranged between 98.37–99.57% for the analysed dataset. Furthermore, the computational performance and accuracy of the proposed methodology in comparison with similar machine learning approaches led to recommending its extension to other applications in achieving highly granular real-time traffic classification, to be used in subsequent user traffic profiling.

4. The investigation, integration and evaluation of user traffic profiling based controls in data center SDN (**chapter 7**). Existing data center (DC) resource provisioning schemes are investigated which predominantly rely on conventional load-balancing technologies utilizing application performance models for traffic optimization. Through profiling user application trends in an enterprise network, it was determined that the diversity in application usage can be extended beyond residential networks towards data center networking and individual application prioritization through conventional load balancing remains a performance caveat for users with varying application trends. Integration of user traffic profiling was, therefore, proposed to capture user application trends within the DC by measuring user traffic flows at the DC edge switches. The resulting profiles were subsequently used to create forwarding policies for external and internal DC traffic. The proposed network-provisioning scheme further allows operators to define a global profile and application hierarchy to prioritize the extracted user traffic classes. The associated traffic management framework uses software defined networking paradigm with OpenFlow protocol to dynamically configure the individual network elements, while tracking real-time profile memberships. Using a sample profile and application priority table and high user load simulations, the design led to superior results when compared to conventional traffic management schemes, offering significantly higher frame delivery ratio (21-39%) and effective throughput (35-37%) for sample priority profiles, despite the inherent link oversubscriptions in the DC. Furthermore, the reduced real-time flow installation and update frequency of the proposed approach offered a substantial decrease in the overall SDN control channel overhead and high design scalability.

5. Investigation and evaluation of an OpenFlow based user traffic profiling solution for campus and enterprise environments (**chapter 8**). Present studies in SDN primarily employ

the control-data plane OpenFlow protocol for real-time reconfiguration and monitoring of SDN switches. In order to allow the use of OpenFlow protocol for enhanced network monitoring and visualization via user traffic profiling, an investigation was undertaken to evaluate whether OpenFlow protocol features may be used to derive per application user traffic flow statistics. A test campus network access switch was used for collection of OpenFlow based traffic statistics and fed into the previously derived traffic profiling mechanism, using k-means cluster analysis for derivation of user profiles based on user generated flow statistics. The derived profiles indicate significant separation among user application trends divided into six user traffic classes which report high level of stability (96.1-99%), making them viable for monitoring purposes. Additional simulation tests at varying user loads attribute minimum computational cost and low additional OpenFlow control overhead (less than 5%) to the proposed approach. While flow records such as NetFlow are directly exported from the networking appliances, the use of OpenFlow enabled traffic profiling results in elimination of separate traffic accounting mechanism using monitoring information directly from the SDN control plane (controller). This is especially of relevance in campus networking where networking devices may be geographically dispersed and can benefit from the centralized user profiling demonstrated offering increased scalability and low management overhead for real-time monitoring and resource provisioning.

A number of papers related to the research project have been presented and published in refereed journal and conferences (Appendix 6). In particular, the author was awarded a best research paper award at the 6th Internet Technologies and Applications Conference (ITA'15). The research presented by this thesis may, therefore, be deemed to have strengthened the SDN traffic engineering domain, especially in the field of user-centric network optimization.

9.2 Limitations of the research project

Despite the research objectives stated above having been met, a number of limitations associated with the project can be identified. The key limitations of the research are summarised as follows.

1. The traffic profiling carried out in **chapter 3** and **chapter 4** primarily relied on application identification through IP address and port mappings. This resulted in a portion of user

application flows in each derived residential user profile falling in the unknown traffic tier. Although the overall percentage of unknown traffic was low in comparison with accurately identified application usage ratio per profile, the resulting user traffic classes could have matched user activities more closely if using layer 7 classification. In order to alleviate the limitations of IP/port classification, manual examination and labelling of unknown traffic flows in the profiling studies was used to improve the accuracy. Furthermore, an independent flow level classifier (**chapter 6**) was designed and evaluated for future use in practical environments where data sources could not be identified merely by relying on IP address and port mappings.

2. The time-frame for traffic flow collection as part of user traffic profiling studies in residential and enterprise environments comprised of durations ranging from a maximum of approximately ten weeks to a minimum of two weeks. Although the collected user traffic statistics contained a significant number of application activities, investigation over a longer profile period accounting for changes in user behaviour, for example, due to vacation or episodes of lower employee attendance in the campus coupled with an understanding of user demographics (age, sex, etc.) would have provided much more insight into the derived user profiles. Such detailed profile analysis may further contribute in aiding operators to design and implement user-centric network policies as well as assess technological and business requirements.

3. The residential SDN traffic management framework (**chapter 5**) utilized average profile flow statistics in computing the required queue rates for per profile bandwidth allocation. While the results reported by the SDN traffic management application offered significant improvement for the chosen profile priority table (sample), a more accurate estimation of queue rates could be obtained by using a probability density function to compute per profile bandwidth utilization and requirement. Therefore, the traffic management application in data center simulations used the maximum probabilities of per profile statistics as a metric in creating external and internal flow constructs tracking real-time profile connections.

4. The test simulations focused on evaluating the core function of network provisioning and performance for the end users allowed by the respective SDN applications. This demonstrated the benefits of user traffic profiling integration in residential, data center

and campus networking controls. However, a more realistic incorporation of the profiling controls in traffic management may require the designed SDN applications to integrate at multiple levels with existing network services. User profile identification in the test simulations, for example, was achieved by allocating respective users known IP address ranges in each profile. The deployed SDN applications could, therefore, track real-time profile memberships by monitoring IP addresses of the respective users. In a realistic implementation, user to profile mapping (owing dynamic IP allocation) would need to be tracked and tied to either existing or new authentication systems (usernames, accounts, Active Directory, LDAP, etc.) or perhaps utilize the tracking of DHCP IP allotments starting from service initiation/ profile derivation. The implementation of the appropriate user identification scheme would depend significantly on the deployed operational setting.

9.3 Suggestions and scope for future work

The research presented by this thesis strengthens the domain of user-centric traffic engineering in software defined networking. Nonetheless, there are a number of areas in which future work could be carried out to further advance upon the findings of this research. The details of future work are listed as follows.

1. Design a modular user-centric SDN application software collection package compatible with multiple controller platforms. This would enable the deployment of user traffic monitoring, profiling and integration of user profiling based controls as a monolithic, yet customizable application ready to be utilized in SDN technology.

2. Extension of the devised flow-based traffic classifier to include more applications by the collection of respective application traffic flows, unsupervised cluster labelling and subsequent employment in classifier training. This would further aid in increasing the real-time user traffic profiling accuracy, especially in residential networking where IP address and port mapping of data sources may not yield a high level of accuracy in identifying user traffic flows. Traffic classification, user profiling and subsequent deployment of user profiling based controls in a live environment would also allow a comprehensive evaluation of the profiling technique based on collecting real participant feedback.

3. Further investigation of the data storage and computational resources required for the user traffic profiles. As the profile derivation was carried out offline on an average machine (PC), the recorded computational cost and storage consumed by the traffic records and subsequent profile statistics did not pose any issue. However, the storage space in residential routers and even carrier grade switches has to be taken into consideration if embedding the respective profiling algorithm and in network appliances. Whilst this is not a particular problem for scenarios where traffic flow measurements utilize an external collector (server) machine also serving as a monitoring station, the storage of traffic profiles, retention of historical statistics, and privacy need to be considered.

4. While the present research mainly concentrated on wired network communication for user traffic profiling and SDN based traffic management, the scheme can be equally implemented in upcoming wireless environments such as 5G mobile networks. Identification of application traffic trends and consequently the derivation of mobile user profiles can help operators in optimizing the traffic of certain user profiles based on business requirements as well as allow a greater range of subscription models targeting user requirements capture through traffic profiling features.

9.4 The future of traffic engineering in SDN

The popularity and development of software defined networking has been steadily increasing since the inception of the paradigm a couple of years ago. An increasing number of operators and organizations are seeking SDN traffic management solutions to meet scalability due to the inherent ease of deploying services owing the real-time network programmability and centralized controlled offered by SDN. As evaluated during user traffic profiling, however, the application diversity among the end users in residential as well as enterprise environments is significant and a fundamental requirement of dynamic service provisioning and resource allocation remains end user satisfaction. Typical traffic engineering in legacy networking as well as SDN though, concentrates on isolated application improvement. A substantial number of earlier studies have hence targeted network optimization of typical time critical applications such as video streaming, VoIP, or generic real-time communication. The traffic management framework and network policies, therefore, lack the level of granularity required to define and construct network policies catering to a wider range of users depicted in the derived traffic profiles.

As the SDN technology progresses and the centralized control framework is extended to other areas, such as high speed mobile services and other legacy installations, the trend to isolate individual services for prioritization will continue to exist. The lack of a standardized northbound SDN control interface means that network control applications continue to be offered and designed as standalone modules that may or may not have any horizontal integration with other SDN services or applications and would therefore make it more difficult for operators to define network policies. However, the performance degradation associated with standalone service optimization may be more significant if the chosen application or service does not comply with end user application trends. In this current context and the foreseeable future, as the technology sees further adoption, the requirement for understanding and capturing user trends for SDN solutions remains significant.

Despite many studies currently undertaken to optimize application traffic flows in SDN, this thesis emphasises the need for a robust and reliable user behaviour profiling mechanism which integrates with SDN technology and offers network administrators in fine tuning resource provisioning according to end user requirements. To this end, this research project investigated the derivation of user traffic profiles in residential as well as enterprise networks and carried out experimentation using several simulation tests to evaluate the viability of incorporating user profiling based resource allocation policies in SDN. The observed results demonstrated significant improvement in network performance metrics for prioritized users (profiles) allowing network administrator to go beyond individual application optimization.

To conclude, understanding user behaviour by profiling users' application trends will be crucial in the near future as more applications and services emerge and the SDN technology matures and finds greater deployment in present network infrastructures. It is envisaged the ever-growing breadth of applications available to end users could become the primary motivation for network administrators to investigate and focus on user trends as a means to design and automate network policy controls.

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APPENDIX – 1

1. **Traffic Classification Script (IP/DNS)**

   1.1 Traffic Classification Script for Residential Users

   1.2 Traffic Classification Script for Enterprise Environment

1.1 IP address Lookup Traffic Classification Script (Residential Users – Chapter 3 and Chapter 4)

```
#! /bin/awk -f
BEGIN {
FS=" ";
}
{

if ($2 !~ /224.0/) {

ips[$1]=$1;
#ipd[$1]=$2;
flows[$1]++;
bytes_as_source[$1]+=$6;
bytes_as_dest[$1]+=$12;
duration_as_source[$1]+=$8;
duration_as_dest[$1]+=$14;
bps_t[$1]+=$9;
bps_r[$1]+=$15;

#General Distribution
if ($5 == 53 ) {dnss[$1]++;}
if ($5 ==80 || $5 ==443 || $5 ~ /8170/ || $5 ~ /8171/) {http[$1]++;}

if ($5 ==20) {ftp[$1]++;}
if ($5 ==21) {ftpc[$1]++;}

#Email

if ($2 ~ /207.46.96.145/ || /209.191.93.53/ ||  /209.131.36.159/ ||
/69.147.114.224/ || /74.125.45.100/ || \
/216.239.34.10/ || /216.239.38.10/ ||  /207.46.105.172/ )
{email_ip[$1]++;}
if ($5 ~ /25/ || $5 ~ /110/ || $5 ~ /587/ || $5 ~ /465/ || $5 ~
/995/ || $5 ~ /993/ || $5 ~ /8089/ || $5 ~ /8096/ )
{email_port[$1]++;}

email[$1] = email_ip[$1]+email_port[$1];

#Social

#if ($2 ~ /^199.16.156/      || /^199.16.159/      || /^31.13.93/
|| /69.63.187.1[6-9]/ || \
#        /69.63.187.2[0-9]/ || /69.63.187.3[0-9]/ || /69.63.189.40/
|| /69.63.176.188/ || \
#       /69.63.178.40/     || /69.63.178.62/     || /69.63.180.4[0-
9]/ || /69.63.180.50/  || /69.63.184.142/    || \
#     /69.63.181.1[0-9]/ || /69.63.181.2[0-9]/ || /69.63.181.3[0-
9]/ || /69.63.181.4[0-9]/ || /69.63.181.50/  ||\
#      /69.63.181.10/     || /74.125.91.191/    ||
/74.125.127.191/  ||  /74.125.159.191/ || /63.135.80.49/   || \
#    /216.178.38.116/   || /168.143.171.84/   || /168.143.161.20/
|| /128.121.146.228/ || /168.143.162.68/ || \
```

```
#  /128.121.243.228/  || /128.121.146.100/  ||  /168.143.162.52/
|| /168.143.162.116/ || /168.143.162.36/ || \
#   /209.237.233.34/   || /68.142.214.24/ ) {social_ip[$1]++;}
#if ($5 ~ /5010/ || $5 ~ /5190/ || $5 ~ /5222/ || $5 ~ /5269/ || $5
~ /3920/ || \
#         $5 ~ /5190/ || $5 ~ /532/ || $5 ~ /119/ || $5 ~ /2195/ ||
$5 ~ /5678/) {social_port[$1]++;}

#          social[$1] = social_ip[$1]+social_port[$1];

#Stream

if ($2 ~ /^173.194.112/       || /^54.244.221/        ||
/74.125.127.100/    || /216.178.40.84/      || /199.181.132.250/
||  /206.220.42.32/ || \
/209.85.227.10[0-2]/ || /209.85.225.10[0-2]/ || /66.102.9.10[0-2]/
|| /216.239.59.10[0-2]/ || /74.125.159.10[0-2]/ || \
/64.233.169.10[0-2]/ || /209.85.135.10[0-2]/ || /74.125.19.10[0-2]/
|| \
/149.126.74.140/     || /82.221.111.20/      ||  /178.236.6.207/
|| /178.236.7.162/      || /176.32.109.244/     || /104.20.5.77/
|| \
/104.20.6.77/        || /104.20.4.77/        || /104.20.7.77/
|| /104.20.31.76/       || /81.17.18.254/       || /69.167.127.57/
|| \
/69.167.127.59/      || /23.61.255.243/      || /23.61.251.99/
|| /195.8.215.137/      || /195.8.215.136/      || /195.8.215.138/
||\
/195.8.215.139/      || /23.61.251.8/        || /23.61.255.241/
|| /2.20.183.162/       || /2.20.183.160/       || /104.28.7.65/
|| /104.28.6.65/   ||\
/54.175.9.128/       || /104.28.20.16/       || /104.28.21.16/
|| /5.79.78.78/         || /74.113.233.128/     || /^216.58.208/
|| /216.58.208.46/ || \
/62.212.83.1/        || /141.0.174.3[4-9]/   || /141.0.174.4[0-4]/
|| /31.192.117.132/     || /31.192.112.104/     || /64.188.63.185/
|| /31.192.116.179/ ) {stream_ip[$1]++;}
if ($5 ~ /8554/ || $5 ~ /1755/ || $5 ~ /7007/ || $5 ~ /1090/ || $5
~ /1900/ || $5 ~ /7070/ || $5 ~ /554/ || $5 ~ /1935/ ||\
$5 ~ /697[0-9]/ || $5 ~ /698[0-9]/ || $5 ~ /7000/ || $5 ~ /5353/ ||
$5 ~ /3689/ || $5 ~ /8088/ || $5 ~ /42000/ || $5 ~ /42999/ )
{stream_port[$1]++;}
stream[$1] = stream_port[$1]+stream_ip[$1];




#Comms

if ($2 ~ /212.8.163.94/   || /157.56.114.105/ || /91.190.218.46/
|| /91.190.216.21/  || /46.105.44.115/  || /54.235.93.201/  ||
/50.16.213.80/ || /86.64.162.35/ || \
/63.111.29.132/  || /198.41.176.169/ || /198.41.180.169/ ||
/198.41.178.169/ || /198.41.179.169/ || /198.41.177.169/ || \
```

```
/69.65.41.15/    || /184.173.191.49/ || /173.239.38.100/ )
{comms_ip[$1]++;}
if ($5 ~ /5060/  || $5 ~ /33033/ || $5 ~ /5351/ || $5 ~ /5050/ ||
$5 ~ /1863/ || $5 ~ /6801/ || \
$5 ~ /10200/ || $5 ~ /1034/ || $5 ~ /1035/ || $5 ~ /2644/ || $5 ~
/8000/      || $5 ~ /9900/      || $5 ~ /9901/      || $5 ~ /8443/
|| \
$5 ~ /2074/  || $5 ~ /2076/ || $5 ~/5061/  || $5 ~/1720/  || $5 ~
/1638[4-9]/ || $5 ~ /1639[0-9]/ || $5 ~ /1640[0-3]/ || $5 ~ /2427/
|| $5 ~ /2944/ || \
$5 ~ /3478/  || $5 ~ /4379/ || $5 ~ /4380/ || $5 ~ /1500/ || $5 ~
/3005/      || $5 ~ /3101/      || $5 ~ /28960/ ||\
$5 ~ /500/   || $5 ~/4500/  || $5 ~ /5060/ || $5 ~ /506[1-9]/ || $5
~ /5070/  || $5 ~/8008/  || $5 ~ /123/ ) {comms_port[$1]++;}

comms[$1]= comms_ip[$1]+comms_port[$1];


#Download

if ($2 ~ /87.248.210.253/ || /87.248.210.254/ || /94.242.253.64/ ||
/94.242.253.65/ || /94.242.253.66/ ||  \
/^108.160.165/   || /154.53.224.142/ || /205.196.120.6/ ||
/205.196.120.8/ || /78.46.142.98/  || \
/144.76.0.3/     || /188.40.125.151/ || \
/109.163.227.73/ || /78.138.99.144/  || /195.3.147.99/   ||
/95.215.61.203/  || /62.210.141.210/ || /178.73.214.217/ ||
/162.159.253.82/ || \
/162.159.254.82/ || /162.159.254.81/ || /162.159.255.81/ ||
/162.159.252.82/ || /91.233.116.126/ || /185.61.148.120/ ||\
/195.85.215.50/  || /82.146.44.36/   || /109.74.151.239/ ||
/95.215.45.119/  || /91.219.238.121/ || /185.25.51.66/   ||
/46.41.129.5/ || \
/151.236.23.10/  || /193.169.189.220/ || /89.46.101.100/ ||
/104.28.29.41/   || /104.28.28.41/   || /198.41.190.233/ ||
/198.41.189.233/ || \
/31.7.59.14/     || /87.248.214.58/  ||\
/188.92.20.182/  || /46.38.62.42/    || /94.242.57.26/   ||
/80.92.65.144/ || /198.41.201.25/ || /198.41.200.25/   || \
/67.23.44.19/    || /31.7.59.14/     || /67.212.76.52/   ||
/5.45.73.241/  || /104.28.27.77/  || /104.28.26.77/    ||
/88.80.6.5/ || \
/198.72.123.87/  || /185.37.100.119/ || /104.28.6.59/    ||
/104.28.7.59/  || /5.45.72.88/    || /195.189.227.28/  || \
/69.172.201.208/ ||  /199.27.135.71/ || /199.27.134.71/  ||
/46.105.165.17/|| /104.28.18.42/   || \
/104.28.19.42/   || /50.56.218.189/  || /72.52.4.120/    ||
/141.101.118.[30-31]/ || /198.41.202.40/ || /198.41.203.40/ || \
/95.215.60.87/   || /66.135.33.31/   || /104.28.10.73/   ||
/104.28.11.73/ || /141.8.225.72/    || /64.182.240.12/ || \
/82.80.246.51/   || /217.70.184.38/  || /104.28.10.69/  ||
/104.28.11.69/  || \
/198.41.200.25/  || /198.41.201.25/  || /198.41.200.42/  ||
/198.41.203.40/  || /67.212.76.52/  ||\
/5.45.72.88/     || /5.45.73.241/ ) {dload_ip[$1]++;}
```

```
if ($5 ~ /688[1-9]/  || $5 ~ /20/ || $5 ~ /21/  || $5 ~ /6346/ ||
$5 ~ /39720/ || $5 ~ /8530/ || \
$5 ~ /5223/ || $5 ~ /69/ || $5 ~ /115/ || $5 ~ /139/  || $5 ~
/7777/ || $5 ~ /548/   || $5 ~ /2336/ || $5 ~ /3004/ || \
$5 ~ /2703[1-9]/ || $5 ~ /2704[0-9]/ || $5 ~ /27050/  || $5 ~
/6881/ || $5 ~ /6459[1-9]/ || $5 ~ /6457[1-9]/ || $5 ~ /6454[1-9]/ )
{dload_port[$1]++;}

dload[$1]=dload_ip[$1]+dload_port[$1];



#Gaming
if ($2 ~ /^199.108.4/    || /^199.108.5/    || /210.175.169.130/ ||
/^198.107.156/    || /^203.105.76/   || \
/23.61.255.224/ || /23.61.255.216/ || /64.30.228.84/    ||
/64.30.228.81/    || /185.31.18.129/ || /185.31.19.192/   ||
/173.192.10.254/ || \
/166.78.41.198/ || /166.78.34.229/ || /166.78.40.244/   ||
/174.143.185.146/ || /162.209.67.97/ || /216.168.44.139/  ||
/64.30.228.82/ ||\
/195.13.205.17/ || /195.13.205.11/ || /89.167.143.67/ ||
/89.167.143.66/   || \
/89.167.143.46/ || /89.167.143.47/ || /67.228.244.148/  ||
/209.34.224.72/   || /166.78.40.244/ || \
/162.209.67.97/ || /166.78.41.198/ || /166.78.41.198/   ||
/64.30.228.82/  || /216.69.227.108/  || \
/195.93.85.49/  || /195.13.205.24/ || /195.13.205.19/   ||
/209.114.51.96/   || /50.19.100.226/ || /74.86.58.192/    ||\
/195.13.205.9/  || /195.13.205.19/ || /64.64.12.224/    ||
/192.33.31.51/    || /104.20.4.17/     || /104.20.5.17/     || \
/173.255.217.211/ || /54.148.109.249/  || /108.162.206.85/ ||
/108.162.205.85/ || \
/104.28.26.119/   || /104.28.27.119/   || /66.216.14.131/  ||
/54.243.154.238/ || /54.208.208.217/ || /88.221.39.235/ || \
/209.200.152.198/ || /134.170.29.210/  || /134.170.29.82/  ||
/64.14.48.177/   || /69.172.201.47/  || /23.46.124.9/ || \
/184.169.130.235/ || /54.195.250.211/ || /54.195.250.208/ ||
/54.248.80.100/  || /184.169.136.110/ || \
/46.30.212.169/ || /194.97.109.24[2-3]/ || /84.45.254.106/ ||
/213.208.119.44/ || /194.105.226.147/ || /84.142.85.2/ ||
/54.248.91.3/ || /174.129.20.105/ ) {game_ip[$1]++;}
if ($5 ~ /4871/ || $5 ~ /5090/ || $5 ~ /32887/ || $5 ~ /32019/ ||
$5 ~/2300/|| $5 ~/3074/ ||\
$5 ~ /1728/ || $5 ~/554/ || $5 ~/2300/ || $5 ~/1935/ || $5 ~/5550/
|| $5 ~/5555/ || $5 ~/18051/ || $5 ~/18055/ || \
$5 ~ /28960/|| $5 ~/6667/ || $5 ~/7777/     || $5 ~ /7778/ || $5 ~
/1640[3-9]/ || $5 ~ /1641[0-9]/ || $5 ~ /1642[0-9]/ ||\
$5 ~ /1643[0-9]/ || $5 ~ /1644[0-9]/ || $5 ~ /1645[0-9]/ || $5 ~
/1646[0-9]/ || $5 ~ /1647[0-2]/ || \
$5 ~ /4380/ || $5 ~ /27000/ || $5 ~ /2700[1-9]/ || $5 ~ /2702[0-9]/
|| $5 ~ /27030/ || \
$5 ~ /3478/ || $5 ~ /3074/ || $5 ~ /3479/ || $5 ~ /3480/ || $5 ~
/9293/ ) {game_port[$1]++;}
```

```
game[$1]=game_ip[$1]+game_port[$1];


#Browsing

if ($5 ==80 || $5 ==443 || $5 ~ /8170/ || $5 ~ /8171/)
{web[$1]=http[$1]-game_ip[$1]-dload_ip[$1]-stream_ip[$1]-
email_ip[$1]-comms_ip[$1];}


}
}

END {

printf ("ipadd\t\tFlows dns web email dload stream games comms
unknown\tTx(s)\tRx(s)\tTx(B)\tRx(B)\tTx(Bps)\tRx(Bps)\n");

for (i in ips) printf
("%s\t%d\t%.1f %.1f %.1f\t%.1f\t%.1f\t%.1f\t%.1f\t%.1f\t%.3f\t%.3f\
t%d\t%d\t%.2f\t%.2f\n",\
ips[i], flows[i], \
dnss[i]/flows[i]*100,\
web[i]/flows[i]*100,\
email[i]/flows[i]*100,\
dload[i]/flows[i]*100,\
stream[i]/flows[i]*100, game[i]/flows[i]*100,\
comms[i]/flows[i]*100, \
unknown[i]=100-
((web[i]/flows[i]*100)+(email[i]/flows[i]*100)+(dnss[i]/flows[i]*10
0)+(game[i]/flows[i]*100)+(dload[i]/flows[i]*100)+(comms[i]/flows[i
]*100)+(stream[i]/flows[i]*100)),\
duration_as_source[i]/flows[i],
duration_as_dest[i]/flows[i],bytes_as_source[i], bytes_as_dest[i],
bps_t[i]/flows[i]/8,bps_r[i]/flows[i]/8); }
```

1.2 Traffic Classification Script (Enterprise Environment – Chapter 7 and Chapter 8)

```
#! /bin/awk -f
BEGIN {
       FS=" ";
       }

{
# As Destination flows, destination IP is inside subnet, source IP
is external
if ($2 ~ /^192.168.200/ && $1 !~ /^192.168.200/)
                        {
                        ipd[$2]=$2;
                        flows_as_dest[$2]++;
                        bytes_as_dest[$2]+=$6;
                        if ($4 ~ /53/ ) {dnsd[$2]++;}
                        if ($4 ~ /80/ || $4 ~ /443/ ) {wwwd[$2]++;}
```

```
                        }

# As Source FLows, source IP inside, destination IP outside subnet
else if ($1 ~ /^192.168.200/ && $2 !~/^192.168.200/ ) {
        ips[$1]=$1;
        flows_as_source[$1]++;
        bytes_as_source[$1]+=$6;

#General Distribution
if ($5 ~ /53/ ) {dnss[$1]++;}
if ($5 ~ /80/ || /443/ ) {http[$1]++;}
if ($5 ~ /20/)  {ftp[$1]++}


#Emailing (MS Office Outlook, SMTP, POP3, IMAP)
if ($2 ~ /141.163.66.145/ ||  /141.163.66.98/ || /141.163.66.99/ ||
$5 ~ /25/ || $5 ~ /110/ || \
         $5 ~ /110/ || $5 ~ /465/ || $5 ~ /995/) {email[$1]++;}


#Storage Services (Virtual Sever Instances, Windows Sever, DB
Storage)
if ($2 ~ /141.163.159.151/ ||  /141.163.159.152/ ||
/141.163.159.153/ || /141.163.159.154/ || /141.163.159.155/ || \
         /141.163.159.161/ ||  /141.163.159.161/ ||
/141.163.159.162/ || /141.163.159.163/) {sts[$1]++;}


#Video Streaming (Online Training, AV and Media Management, AV
Content Capture)
if ($2 ~ /141.101.127.128/ ||  /141.163.10.6/ || /141.163.1.250/ ||
/141.163.159.150/ || /141.163.79.196/ || \
         /141.163.79.197/  ||  /141.163.79.199/) {vds[$1]++;}

#Communications (Office Communications Services)
if ($2 ~ /141.163.159.33/   ||  /141.163.159.8/   ||
/141.163.160.3/   || /141.163.161.2/   || /141.163.161.3/ || \
         /141.163.163.171/  ||  /141.163.163.241/ ||
/141.163.201.221/ || /141.163.201.222/ || /141.163.222.100/)
{comms[$1]++;}

#Enterprise (Corporate Information Systems, Staff Portal, E-
Portfolio)
if ($2 ~ /141.163.222.101/ || /141.163.222.102/ ||
/141.163.222.112/|| /141.163.222.14/ || /141.163.222.160/ || \
         /141.163.222.166/ || /141.163.222.33/  || /141.163.222.43/
|| /141.163.222.91/ || /141.163.231.102/ || \
            /141.163.231.198/ || /141.163.231.241/ ||
/141.163.231.93/ || /141.163.231.94/ || /141.8.226.14/ ||
/141.85.216.241/) {etp[$1]++;}

#Publishing (Content Management System, Document Scanning and
Printing)
if ($2 ~ /141.163.231.96/ || /141.163.236.221/ ||
/141.163.246.123/|| /141.163.246.124/ || /141.163.254.160/ || \
```

```
         /141.163.66.102/ || /192.168.135.122/  ||
/192.168.135.127/) {pub[$1]++;}

#Software Services (Software Distribution Service, Specialist
Software Services)
if ($2 ~ /141.163.66.130/ || /141.163.66.131/ || /141.163.66.132/||
/141.163.66.134/) {sfs[$1]++;}

#Web Browsing (Internet Traffic)
if ($5 ==80 || $5 ==443 && http[$1] > email[$1] && http[$1] >
sts[$1] && http[$1] > vds[$1] && http[$1] > comms[$1] && http[$1] >
etp[$1] && http[$1] > pub[$1] && http[$1] > sfs[$1] )
{web[$1]=http[$1]-email[$1]-sts[$1];}

#Internal,external website
#if ($2 ~ /141.163.1.14/ || /141.163.1.15/ || /172.20.0.97/|| /
#172.20.4.9/ || /172.20.7.2/) {web[$1]++;}


}
}

END {

printf ("ipadd\t\tflows dns web email sts vds comms etp pub sfs\t
Tx(s)\tRx(s)\tTx(B)\tRx(B)\tTx(Bps)\tRx(Bps) \n");

for (i in ips) printf
("%s\t%d\t%.1f %.1f %.1f\t%.1f\t%.1f\t%.1f\t%.1f\t%.1f\t%.1f\t%.1f\
t%.1f\t%.1f\t%.1f\t%.1f\n",\
ips[i], flows[i], dnss[i]/flows[i]*100,
web[i]/flows[i]*100,email[i]/flows[i]*100, sts[i]/flows[i]*100,
vds[i]/flows[i]*100, comms[i]/flows[i]*100, etp[i]/flows[i]*100,
pub[i]/flows[i]*100, sfs[i]/flows[i]*100, \
duration_as_source[i]/flows[i],
duration_as_dest[i]/flows[i],bytes_as_source[i], bytes_as_dest[i],
bps_t[i]/flows[i]/8, bps_r[i]/flows[i]/8);
}
```

APPENDIX – 2

2. <u>Cluster Analysis Scripts</u>

2.1 K-Means Cluster Analysis (R-Code)

2.2 Hierarchical Cluster Analysis (R-Code)

2.3 DBSCAN Clsuter Analysis (R-Code)

2.4 Automated Profiler (BASH)

2.1 K-Means Clustering (Chapter 3 and Chapter 4)

```
***Calculating correct value of k***

analysis.features <- scale (analysis.features) #Optional
wss <- (nrow(analysis.features)-
1)*sum(apply(analysis.features,2,var))
for (i in 2:15) wss[i] <-
sum(kmeans(analysis.features,centers=i)$withinss)
plot(1:15, wss, type="o", xlab="Number of Clusters(k)",
ylab="Within groups sum of squares(wss)", lty=3, cex =0.6,
cex.axis=0.7, cex.main=0.7, cex.lab=0.7)

***Deriving Clusters based on the graphical 'knee in graph' value
of k ***

analysis_month =
read.csv("C:/Users/tbakhshi/Downloads/project2/Complete_Profiling/m
onth_report.csv")
analysis.features= analysis_month
analysis.features$date <- NULL
analysis.features$time <- NULL
analysis.features$srcip <- NULL
analysis.features$dstip <- NULL
analysis.features$srcp <- NULL
analysis.features$dstp <- NULL
analysis.features$In_dur <- NULL
View(analysis.features)
profiles <- kmeans (analysis.features, 6)
profiles
print ("***PROFILING WITH 6 CLUSTERS***")
print (profiles)
table1 <- table(analysis_month$ipadd, profiles$cluster,
analysis_month$Date)
print(table1)
table2 <- table(analysis_month$User, profiles$cluster,
analysis_month$Date)
print(table2)

sink("C:/Users/tbakhshi/Downloads/project2/clusters-flows_6.txt" ,
append=TRUE)
```

2.2 Hierarchical Clustering (Chapter 4)

```
applications =
read.csv("C:/Users/tbakhshi/Downloads/Project2/v2/report_month_non_
neg.csv")
View (applications)
applications.features=applications
applications.features$ipadds <- NULL
applications.features$Flows <- NULL
```

```
applications.features$Tx.s. <- NULL
applications.features$Rx.s. <- NULL
applications.features$Tx.B. <- NULL
applications.features$Rx.B. <- NULL
applications.features$Tx.Bps. <- NULL
applications.features$Rx.Bps. <- NULL
applications.features$dns <- NULL
applications.features$Date <- NULL
applications.features$Port <- NULL
applications.features$Gateway <- NULL
applications.features$User <- NULL
View (applications.features)
library (cluster)
applications.features.dist=dist(applications.features)
applications.features.hclust = hclust(applications.features.dist,
method=ward)
plot(applications.features.hclust,labels=applications$ipadds,main='
Default from hclust')
groups.6 = cutree(applications.features.hclust,6)
sapply(unique(groups.6),function(g)applications$ipadds[groups.6 ==
g])
aggregate(applications.features,list(groups.6),median)

***To check what would be the potential cluster sizes between 2 and
6***
counts =
sapply(2:6,function(ncl)table(cutree(applications.features.hclust,n
cl)))
names(counts) = 2:6
counts
```

2.3 DBSCAN Clustering (Chapter 4)

```
library("dbscan", lib.loc="~/R/win-library/3.2")
library (fpc)
kNNdistplot(d, k = 5)
abline(h=10, col = "red", lty=2)
abline(h=12, col = "red", lty=2)
abline(h=8, col = "red", lty=2)
res <- dbscan(d, eps = 8)

DBSCAN clustering for 10095 objects.
Parameters: eps = 8, minPts = 5
The clustering contains 17 cluster(s) and 327 noise points.
   0    1    2    3    4    5    6    7    8    9   10   11   12
13   14   15   16   17
 327 9396  183   47   23    4   36   13    5   13    7    7    5
7    5    5    7    5

res <- dbscan(d, eps = 10)
res
DBSCAN clustering for 10095 objects.
Parameters: eps = 10, minPts = 5
The clustering contains 15 cluster(s) and 190 noise points.
```

```
   0    1    2    3    4    5    6    7    8    9   10   11   12
13   14   15
 190 9530  186   51   23    9   37    6    6   13   13    8    6
7    6    4

Available fields: cluster, eps, minPts


res <- dbscan(d, eps = 12)
res
DBSCAN clustering for 10095 objects.
Parameters: eps = 12, minPts = 5
The clustering contains 11 cluster(s) and 111 noise points.

   0    1    2    3    4    5    6    7    8    9   10   11
 111 9621  195   74   28   17   19   11    3    6    5    5

Available fields: cluster, eps, minPts

Changing minPts:

> res <- dbscan(d, eps = 12, minPts = 10)
> res
DBSCAN clustering for 10095 objects.
Parameters: eps = 12, minPts = 10
The clustering contains 5 cluster(s) and 244 noise points.

   0    1    2    3    4    5
 244 9571  186   63   17   14

Available fields: cluster, eps, minPts

> res <- dbscan(d, eps = 12, minPts = 50)
> res
DBSCAN clustering for 10095 objects.
Parameters: eps = 12, minPts = 50
The clustering contains 3 cluster(s) and 553 noise points.

   0    1    2    3
 553 9241  124  177

Available fields: cluster, eps, minPts


> res <- dbscan(d, eps = 8, minPts = 10)
> res
DBSCAN clustering for 10095 objects.
Parameters: eps = 8, minPts = 10
The clustering contains 10 cluster(s) and 490 noise points.

   0    1    2    3    4    5    6    7    8    9   10
 490 9152  130  176   36   23   36   14   13   13   12

Available fields: cluster, eps, minPts
```

```
> res <- dbscan(d, eps = 8, minPts = 50)
> res
DBSCAN clustering for 10095 objects.
Parameters: eps = 8, minPts = 50
The clustering contains 4 cluster(s) and 1060 noise points.

   0    1    2    3    4
1060 8169  113  621  132

Available fields: cluster, eps, minPts

> res <- dbscan(d, eps = 10, minPts = 10)
> res
DBSCAN clustering for 10095 objects.
Parameters: eps = 10, minPts = 10
The clustering contains 7 cluster(s) and 329 noise points.

   0    1    2    3    4    5    6    7
 329 9457  184   39   23   37   13   13

Available fields: cluster, eps, minPts

> res <- dbscan(d, eps = 10, minPts = 50)
> res
DBSCAN clustering for 10095 objects.
Parameters: eps = 10, minPts = 50
The clustering contains 3 cluster(s) and 724 noise points.

   0    1    2    3
 724 9079  124  168

Available fields: cluster, eps, minPts
```

2.4 Automated Profiler (BASH Scripts)

(a) Flow Records Concatenation Script

[Input: NetFlow, OpenFlow statistics. Output: Application Usage Report Per User]

```
#!/bin/bash


for dom in {01..31};
do
flow-cat ft-v05.2015-01-$dom.* > ftlog01$dom.dat;
ft2nfdump -r ftlog01$dom.dat | nfdump -w nflog01$dom.dat;
nfdump -r nflog01$dom.dat -o
"fmt:%sa %da %pr %sp %dp %byt %pkt %td %bps %pps %bpp %fl" -q >
raw_data01$dom.dat
cat raw_data01$dom.dat| awk -f bytes.awk | sed "s/M//g" | column -
t > fmt_data01$dom.dat
cat fmt_data01$dom.dat| awk '$2 ~ /^192.168/ && $1 !~ /^192.168/
{print $0}' > incoming$dom.dat
```

```
cat fmt_data01$dom.dat | awk '$1 ~ /^192.168/ && $2 !~/^192.168/ &&
$2 !~ /^224.0/ {print $0}' > outgoing$dom.dat
awk
'NR==FNR{a[$2,$1,$5,$4]=$20FS$6"\t"$7"\t"$8"\t"$9"\t"$10"\t"$11\t"$
12";next}{$21=a[$1,$2,$4,$5];print}' OFS=' ' incoming$dom.dat
outgoing$dom.dat | column -t > flowrecords$dom.dat

#using the application identifaction script from appendix: 1.1, 1.2.

cat flowrecords$dom.dat | awk -f nfprofiler.awk | column -t >
report01_$dom;
rm ftlog01$dom.dat nflog01$dom.dat raw_data01$dom.dat
fmt_data01$dom.dat incoming$dom.dat outgoing$dom.dat
flowrecords$dom.dat;

done;

cat report01_$dom | awk '$10 <= 10.50 && $10 > 0 {print $0}' | tr
'\t' ',' > log$dom.csv
cat log$dom.csv >> data.csv # (Application Usage Report)
```

(b) K-Means Cluster Analysis Script(s)

[Input: Application Usage Report. Output: Clusters (profiles) and Flow Statistics]

wss.sh

```
#!/bin/bash
./wss_calculator.r > wss_file.raw
cat wss_file.raw | awk '{print $2" "$3" "$4" "$5" "$6" "$7}' |
xargs > wss_file.new
awk '{for (i=1;i<=NF;i++) {print $i}}' wss_file.new > wss_file.dat
awk '{print NR, $0}' wss_file.dat > wss_plot.dat
rm wss_file.raw wss_file.new wss_file.dat
gnuplot plotscript
```

wss_calculator.r

```
#!/usr/bin/env Rscript
# R code goes here
d = read.csv ("data.csv")
#View (d)
d.app <- d[4:11]
#View (d.app)
wss_app <- (nrow(d.app)-1)*sum(apply(d.app,2,var))
for (i in 2:20) wss_app[i] <- sum(kmeans(d.app, centers=i,
iter.max=30)$withinss)
wss_app
./cluster_calculator.r > profiles.dat
cat profiles.dat
```

plotscript

```
# Scale font and line width (dpi) by changing the size! It will
always display stretched.
set terminal svg size 400,300 enhanced fname 'arial'  fsize 10 butt
solid
set output 'out.svg'
# Key means label...
set key inside bottom right
set xlabel 'k'
set ylabel 'wss. vs. k'
set title 'Wss vs. k'
plot  "wss_plot.dat" using 1:2 title 'wss. vs k' with lines
pause -1 "Hit any key to continue"
```

profiler.sh

```
#!/usr/bin/bash
./cluster_calculator.r > cluster.raw

cat cluster.raw | sed -n -e '/Cluster/,$p' | sed -e
'/Clustering/,$d' > /home/controller/results/cluster_result.dat;
cat cluster.raw | grep between_SS >>
/home/controller/results/cluster_result.dat;
cat cluster.raw | sed -e '1,/table/d' | sed -e '/>/,$d' | sed
'/^\s*$/d' | sed  '1s/^/ipadd /' | column -t | tr -s ' ' ',' >
/home/controller/results/clusteredfile.csv;
done;

echo
========================================================================
echo "CLUSTERS:"
echo
========================================================================
cat /home/controller/results/cluster_result.dat

awk 'NR==FNR{a[$1]=$19FS$2","$3;next}{$17=a[$1];print}' FS=','
/home/controller/results/clusteredfile.csv report.csv | tr -s ' '
',' > complete_report.csv
```

cluster_calculator.r

```
#!/usr/bin/env Rscript
d=read.csv ("data.csv")
d.app <- d[4:11]
app_cluster_k = kmeans (d.app, 4)# sample for four profiles
app_cluster_k
```

APPENDIX – 3

3. Machine Learning based Traffic Classification

3.1 K-Means Cluster Analysis (wss. Vs. k) per application (R-Code)

3.2 C.50 Classifier Training (Chapter 6)

3.3 C.50 Classifier Decision Tree Derivation (R-Code)

3.1 Machine Learning based Traffic Classification (Chapter 6)

```
***Calculating clusters vs. wss graph for each application ***

analysis_month =
read.csv("C:/Users/tbakhshi/Downloads/Project3/email.csv")
View (analysis_month)
email.features = analysis_month
email.features $sno <- NULL
email.features $SrcIP <- NULL
email.features $DstIP <- NULL
email.features $SrcPo <- NULL
email.features $DstPo <- NULL
email.features $Prot. <- NULL
View (email.features)

email.features .features <- scale (email.features) #Optional
wss <- (nrow(email.features)-1)*sum(apply(email.features ,2,var))
for (i in 2:10) wss[i] <-
sum(kmeans(email.features,centers=i)$withinss)
plot(1:10, wss, type="o", xlab="Number of Clusters(k)",
ylab="Within groups sum of squares(wss)", lty=3, cex =0.6,
cex.axis=0.7, cex.main=0.7, cex.lab=0.7)

analysis_month =
read.csv("C:/Users/tbakhshi/Downloads/Project3/game.csv")
View (analysis_month)
game.features = analysis_month
game.features$sno <- NULL
game.features$SrcIP <- NULL
game.features$DstIP <- NULL
game.features$SrcPo <- NULL
game.features$DstPo <- NULL
game.features$Prot. <- NULL
View (game.features)

game.features <- scale (game.features) #Optional
wss <- (nrow(game.features)-1)*sum(apply(game.features,2,var))
for (i in 2:10) wss[i] <-
sum(kmeans(game.features,centers=i)$withinss)
plot(1:10, wss, type="o", xlab="Number of Clusters(k)",
ylab="Within groups sum of squares(wss)", lty=3, cex =0.6,
cex.axis=0.7, cex.main=0.7, cex.lab=0.7)

analysis_month =
read.csv("C:/Users/tbakhshi/Downloads/Project3/stream1.csv")
View (analysis_month)
stream1.features = analysis_month
stream1.features$sno <- NULL
stream1.features$SrcIP <- NULL
stream1.features$DstIP <- NULL
stream1.features$SrcPo <- NULL
stream1.features$DstPo <- NULL
stream1.features$Prot. <- NULL
View (stream1.features)
```

```
analysis_month =
read.csv("C:/Users/tbakhshi/Downloads/Project3/storage.csv")
View (analysis_month)
storage.features = analysis_month
storage.features$sno <- NULL
storage.features$SrcIP <- NULL
storage.features$DstIP <- NULL
storage.features$SrcPo <- NULL
storage.features$DstPo <- NULL
storage.features$Prot. <- NULL
View (storage.features)

dropbox.features <- scale (storage.features) #Optional
wss <- (nrow(storage.features)-1)*sum(apply(storage.features,2,var))
for (i in 2:10) wss[i] <-
sum(kmeans(storage.features,centers=i)$withinss)
plot(1:10, wss, type="o", xlab="Number of Clusters(k)",
ylab="Within groups sum of squares(wss)", lty=3, cex =0.6,
cex.axis=0.7, cex.main=0.7, cex.lab=0.7)


analysis_month =
read.csv("C:/Users/tbakhshi/Downloads/Project3/torrents.csv")
View (analysis_month)
torrents.features = analysis_month
torrents.features$sno <- NULL
torrents.features$SrcIP <- NULL
torrents.features$DstIP <- NULL
torrents.features$SrcPo <- NULL
torrents.features$DstPo <- NULL
torrents.features$Prot. <- NULL
torrents.features$Tag <- NULL
View (torrents.features)

torrents.features <- scale (torrents.features) #Optional
wss <- (nrow(torrents.features)-
1)*sum(apply(torrents.features,2,var))
for (i in 2:10) wss[i] <-
sum(kmeans(torrents.features,centers=i)$withinss)
plot(1:10, wss, type="o", xlab="Number of Clusters(k)",
ylab="Within groups sum of squares(wss)", lty=3, cex =0.6,
cex.axis=0.7, cex.main=0.7, cex.lab=0.7)

analysis_month =
read.csv("C:/Users/tbakhshi/Downloads/Project3/comms.csv")
View (analysis_month)
comms.features = analysis_month
comms.features$sno <- NULL
comms.features$SrcIP <- NULL
comms.features$DstIP <- NULL
comms.features$SrcPo <- NULL
comms.features$DstPo <- NULL
comms.features$Prot. <- NULL
comms.features$Tag <- NULL
View (comms.features)
```

```
comms.features <- scale (comms.features) #Optional
wss <- (nrow(comms.features)-1)*sum(apply(comms.features,2,var))
for (i in 2:10) wss[i] <-
sum(kmeans(comms.features,centers=i)$withinss)
plot(1:10, wss, type="o", xlab="Number of Clusters(k)",
ylab="Within groups sum of squares(wss)", lty=3, cex =0.6,
cex.axis=0.7, cex.main=0.7, cex.lab=0.7)


***Run clusters <- kmeans (k, Application_Data)for each set of
application flows as per computation of k***
```

3.2 C.50 Classifier Training (Chapter 6)

```
****IMPLEMENTING C50 IN R****
***IN R AFTER ADDING FUNCTION C5.0.GRAPHVIZ AND LIBRARY(C50)
applications =
read.csv("C:/Users/tbakhshi/Downloads/applications.csv")
View (applications)
X <- applications[,1:15] #Feature Set
Y <- applications[,16]   #Comparison/Classification Vector
treeModel <- C50::C5.0(X, Y, control= C5.0Control(minCases = 1,
fuzzyThreshold = TRUE, noGlobalPruning = FALSE))
summary (treeModel)
C5.0.graphviz(treeModel,
"C:/Users/tbakhshi/Downloads/Project3/c50.txt")
***IN LINUX***
ubuntu@ubuntu:/mnt/hgfs/Downloads$ dot -Tpng c50.txt > output.png
****Analysing Confusion Matrix****

applications =
read.csv("C:/Users/tbakhshi/Downloads/Project3/dataset3.csv")
X <- applications[,3:17] #Feature Set
Y <- applications[,18]   #Comparison/Classification Vector
trainx <- X[1:210600,]
trainy <- Y[1:210600]
testx <- X[210700:421300,]
testy <- Y[210700:421300]
treeModel <- C50::C5.0(trainx, trainy, control=
C5.0Control(minCases = 1, fuzzyThreshold = TRUE, noGlobalPruning =
FALSE, winnow=TRUE))
summary (treeModel)

p <- predict(treeModel, testx, type="class" )
sum( p == testy ) / length( p )

confusionMatrix (p, testy)

Case 1
treeModel <- C50::C5.0(trainx, trainy, control=
C5.0Control(minCases = 1, fuzzyThreshold = TRUE, noGlobalPruning =
FALSE, winnow=TRUE))
```

```
p <- predict(treeModel, testx, type="class" )
sum( p == testy ) / length( p )
Case 2
treeModel <- C50::C5.0(trainx, trainy, trials=10, control=
C5.0Control(minCases = 1, fuzzyThreshold = TRUE, noGlobalPruning =
FALSE, winnow=TRUE, earlyStopping=TRUE))
p <- predict(treeModel, testx, type="class" )
sum( p == testy ) / length( p )
Case 3
treeModel <- C50::C5.0(trainx, trainy, control=
C5.0Control(minCases = 1, fuzzyThreshold = TRUE, noGlobalPruning =
TRUE, winnow=TRUE))
p <- predict(treeModel, testx, type="class" )
sum( p == testy ) / length( p )
Case 4
treeModel <- C50::C5.0(trainx, trainy, trials=10, control=
C5.0Control(minCases = 1, fuzzyThreshold = TRUE, noGlobalPruning =
TRUE, winnow=TRUE, earlyStopping=TRUE))
p <- predict(treeModel, testx, type="class" )
sum( p == testy ) / length( p )

>  sensitivity <- senspec [,c(2)]
>  specificity <- senspec [,c(3)]
>  height <- rbind (sensitivity, specificity)
> mp <- barplot(height, beside = TRUE, cex =0.8, cex.axis=1,
cex.main=1, cex.lab=1, ylim = c(0, 1), xlab = "Flow Classes", ylab
= "Sensitivity / Specificity Value", names.arg = senspec$FlowClass,
legend.text =TRUE, args.legend = locator(1))
> applications =
read.csv("C:/Users/tbakhshi/Downloads/Project3/dataset3.csv")
> View (applications)
> applications =
read.csv("C:/Users/tbakhshi/Downloads/Project3/dataset2.csv")
> View (applications)
```

3.3 C.50 Classifier Decision Tree Derivation (Chapter 6)

```
#-----------------------------------------------------------#
# This code implements C5.0.graphviz conversion routine   #
#-----------------------------------------------------------#

C5.0.graphviz <- function( C5.0.model, filename, fontname
='Arial',col.draw ='black',
col.font ='blue',col.conclusion ='lightpink',col.question =
'grey78',
shape.conclusion ='box3d',shape.question ='diamond',
bool.substitute = 'None', prefix=FALSE, vertical=TRUE ) {

library(cwhmisc)
library(stringr)
treeout <- C5.0.model$output
treeout<- substr(treeout, cpos(treeout, 'Decision tree:',
start=1)+14,nchar(treeout))
```

```
treeout<- substr(treeout, 1,cpos(treeout, 'Evaluation on training
data', start=1)-2)
variables <- data.frame(matrix(nrow=500, ncol=4))
names(variables) <- c('SYMBOL','TOKEN', 'TYPE' , 'QUERY')
connectors <- data.frame(matrix(nrow=500, ncol=3))
names(connectors) <- c('TOKEN', 'START','END')
theStack <- data.frame(matrix(nrow=500, ncol=1))
names(theStack) <- c('ITEM')
theStackIndex <- 1
currentvar <- 1
currentcon <- 1
open_connection <- TRUE
previousindent <- -1
firstindent <- 4
substitutes <- data.frame(None=c('= 0','= 1'), yesno=c('no','yes'),
truefalse=c('false', 'true'),TF=c('F','T'))
dtreestring<-unlist( scan(text= treeout,   sep='\n', what
=list('character')))

for (linecount in c(1:length(dtreestring))) {
lineindent<-0
shortstring <- str_trim(dtreestring[linecount], side='left')
leadingspaces <- nchar(dtreestring[linecount]) - nchar(shortstring)
lineindent <- leadingspaces/4
dtreestring[linecount]<-str_trim(dtreestring[linecount],
side='left')
while (!is.na(cpos(dtreestring[linecount], ':   ', start=1)) ) {
lineindent<-lineindent + 1
dtreestring[linecount]<-substr(dtreestring[linecount],
ifelse(is.na(cpos(dtreestring[linecount], ':   ', start=1)), 1,
cpos(dtreestring[linecount], ':   ', start=1)+4),
nchar(dtreestring[linecount]) )
shortstring <- str_trim(dtreestring[linecount], side='left')
leadingspaces <- nchar(dtreestring[linecount]) - nchar(shortstring)
lineindent <- lineindent + leadingspaces/4
dtreestring[linecount]<-str_trim(dtreestring[linecount],
side='left')
}
if (!is.na(cpos(dtreestring[linecount], ':...', start=1)))
lineindent<- lineindent +  1
dtreestring[linecount]<-substr(dtreestring[linecount],
ifelse(is.na(cpos(dtreestring[linecount], ':...', start=1)), 1,
cpos(dtreestring[linecount], ':...', start=1)+4),
nchar(dtreestring[linecount]) )
dtreestring[linecount]<-str_trim(dtreestring[linecount])
stringlist <- strsplit(dtreestring[linecount],'\\:')
stringpart <- strsplit(unlist(stringlist)[1],'\\s')
if (open_connection==TRUE) {
variables[currentvar,'TOKEN'] <- unlist(stringpart)[1]
variables[currentvar,'SYMBOL'] <-
paste('node',as.character(currentvar), sep='')
variables[currentvar,'TYPE'] <- shape.question
variables[currentvar,'QUERY'] <- 1
   theStack[theStackIndex,'ITEM']<-variables[currentvar,'SYMBOL']
theStack[theStackIndex,'INDENT'] <-firstindent
```

```
theStackIndex<-theStackIndex+1
currentvar <- currentvar + 1
if(currentvar>2) {
  connectors[currentcon - 1,'END'] <- variables[currentvar - 1,
'SYMBOL']
}
   }
connectors[currentcon,'TOKEN'] <-
paste(unlist(stringpart)[2],unlist(stringpart)[3])
if (connectors[currentcon,'TOKEN']=='= 0')
connectors[currentcon,'TOKEN'] <-
as.character(substitutes[1,bool.substitute])
if (connectors[currentcon,'TOKEN']=='= 1')
connectors[currentcon,'TOKEN'] <-
as.character(substitutes[2,bool.substitute])
if (open_connection==TRUE) {
if (lineindent<previousindent) {
theStackIndex <- theStackIndex-(( previousindent- lineindent)  +1 )
currentsymbol <-theStack[theStackIndex,'ITEM']
} else
currentsymbol <-variables[currentvar - 1,'SYMBOL']
} else {
currentsymbol <-theStack[theStackIndex-((previousindent -
lineindent ) +1    ),'ITEM']
theStackIndex <- theStackIndex-(( previousindent- lineindent)    )
}
connectors[currentcon, 'START'] <- currentsymbol
currentcon <- currentcon + 1
open_connection <- TRUE
if (length(unlist(stringlist))==2) {
 stringpart2 <- strsplit(unlist(stringlist)[2],'\\s')
variables[currentvar,'TOKEN'] <-
paste(ifelse((prefix==FALSE),'','Class'), unlist(stringpart2)[2])
variables[currentvar,'SYMBOL'] <-
paste('node',as.character(currentvar), sep='')
variables[currentvar,'TYPE'] <- shape.conclusion
variables[currentvar,'QUERY'] <- 0
currentvar <- currentvar + 1
connectors[currentcon - 1,'END'] <- variables[currentvar -
1,'SYMBOL']
open_connection <- FALSE
}
previousindent<-lineindent
}
runningstring <- paste('digraph g {', 'graph ', sep='\n')
runningstring <- paste(runningstring, ' [rankdir="', sep='')
runningstring <- paste(runningstring,
ifelse(vertical==TRUE,'TB','LR'), sep='' )
runningstring <- paste(runningstring, '"]', sep='')
  for (lines in c(1:(currentvar-1))) {
  runningline <- paste(variables[lines,'SYMBOL'], '[shape="')
  runningline <- paste(runningline,variables[lines,'TYPE'], sep='' )
  runningline <- paste(runningline,'" label ="', sep='' )
  runningline <- paste(runningline,variables[lines,'TOKEN'],
sep='' )
```

```
  runningline <- paste(runningline,
  '" style=filled fontcolor=', sep='')
  runningline <- paste(runningline, col.font)
  runningline <- paste(runningline,' color=' )
  runningline <- paste(runningline, col.draw)
  runningline <- paste(runningline,' fontname=')
  runningline <- paste(runningline, fontname)
  runningline <- paste(runningline,' fillcolor=')
  runningline <- paste(runningline,
  ifelse(variables[lines,'QUERY']== 0 ,col.conclusion,col.question))
  runningline <- paste(runningline,'];')
  runningstring <- paste(runningstring, runningline , sep='\n')
  }
  for (lines in c(1:(currentcon-1))) {
  runningline <- paste (connectors[lines,'START'], '->')
  runningline <- paste (runningline, connectors[lines,'END'])
  runningline <- paste (runningline,'[label="')
  runningline <- paste (runningline,connectors[lines,'TOKEN'],
sep='')
  runningline <- paste (runningline,'" fontname=', sep='')
  runningline <- paste (runningline, fontname)
  runningline <- paste (runningline,'];')
  runningstring <- paste(runningstring, runningline , sep='\n')
  }
runningstring <- paste(runningstring,'}')
cat(runningstring)
  sink(filename, split=TRUE)
cat(runningstring)
sink()
}
```

APPENDIX – 4

4. Mininet Topologies

4.1 Residential Network Topology

4.2 Data Center Network Topology

4.3 Campus Network Topology – Profiling Overead Computation

4.1 Residential Network Topology (Chapter 5)

```
#!/usr/bin/python

"""
Script created by VND - Visual Network Description (SDN version)
"""
from mininet.net import Mininet
from mininet.node import Controller, RemoteController,
OVSKernelSwitch, IVSSwitch, UserSwitch
from mininet.link import Link, TCLink
from mininet.cli import CLI
from mininet.log import setLogLevel

def topology():

    "Create a network."
    net = Mininet( controller=RemoteController, link=TCLink,
switch=OVSKernelSwitch )

    print "*** Creating nodes"
    s1 = net.addSwitch( 's1', listenPort=6673,
mac='00:00:00:00:00:01' )
    s2 = net.addSwitch( 's2', listenPort=6674,
mac='00:00:00:00:00:02' )
    h3 = net.addHost( 'h3', mac='00:00:00:00:00:03',
ip='10.0.0.3/8' )
    h4 = net.addHost( 'h4', mac='00:00:00:00:00:04',
ip='10.0.0.4/8' )
    h5 = net.addHost( 'h5', mac='00:00:00:00:00:05',
ip='10.0.0.5/8' )
    h6 = net.addHost( 'h6', mac='00:00:00:00:00:06',
ip='10.0.0.6/8' )
    h7 = net.addHost( 'h7', mac='00:00:00:00:00:07',
ip='10.0.0.7/8' )
    h8 = net.addHost( 'h8', mac='00:00:00:00:00:08',
ip='10.0.0.8/8' )
    h9 = net.addHost( 'h9', mac='00:00:00:00:00:09',
ip='10.0.0.9/8' )
    h10 = net.addHost( 'h10', mac='00:00:00:00:00:10',
ip='10.0.0.10/8' )
    c20 = net.addController( 'c20' )
    h22 = net.addHost( 'h22', mac='00:00:00:00:00:22',
ip='10.0.0.22/8' )
    h23 = net.addHost( 'h23', mac='00:00:00:00:00:23',
ip='10.0.0.23/8' )
    h24 = net.addHost( 'h24', mac='00:00:00:00:00:24',
ip='10.0.0.24/8' )
    h25 = net.addHost( 'h25', mac='00:00:00:00:00:25',
ip='10.0.0.25/8' )

    print "*** Creating links"
    net.addLink(h25, s1, 0, 13)
    net.addLink(h24, s1, 0, 12)
    net.addLink(s1, h23, 11, 0)
```

```
    net.addLink(h22, s1, 0, 10)
    net.addLink(s1, s2, 9, 3)
    net.addLink(s2, h5, 2, 0)
    net.addLink(s1, h10, 8, 0)
    net.addLink(s1, h9, 7, 0)
    net.addLink(s1, h8, 6, 0)
    net.addLink(s1, h7, 5, 0)
    net.addLink(s1, h6, 4, 0)
    net.addLink(s1, h4, 3, 0)
    net.addLink(s1, h3, 2, 0)
    net.addLink(s1, s2, 1, 1)

    print "*** Starting network"
    net.start()
    c20.start()

    print "*** Running CLI"
    CLI( net )

    print "*** Stopping network"
    net.stop()

if __name__ == '__main__':
    setLogLevel( 'info' )
    topology()
```

4.2 Data Center Network Topology (Chapter 7)

```
#!/usr/bin/python

"""
Script created by VND - Visual Network Description (SDN version)
"""
from mininet.net import Mininet
from mininet.node import Controller, RemoteController,
OVSKernelSwitch, IVSSwitch, UserSwitch
from mininet.link import Link, TCLink
from mininet.cli import CLI
from mininet.log import setLogLevel

def topology():

    "Create a network."
    net = Mininet( controller=Controller, link=TCLink,
switch=OVSKernelSwitch )

    print "*** Creating nodes"
    s1 = net.addSwitch( 's1', protocols='OpenFlow10',
listenPort=6673, mac='00:00:00:00:00:01' )
    s2 = net.addSwitch( 's2', protocols='OpenFlow10',
listenPort=6674, mac='00:00:00:00:00:02' )
    s3 = net.addSwitch( 's3', protocols='OpenFlow10',
listenPort=6675, mac='00:00:00:00:00:03' )
```

```
    s4 = net.addSwitch( 's4', protocols='OpenFlow10',
listenPort=6676, mac='00:00:00:00:00:04' )
    s5 = net.addSwitch( 's5', protocols='OpenFlow10',
listenPort=6677, mac='00:00:00:00:00:05' )
    s6 = net.addSwitch( 's6', protocols='OpenFlow10',
listenPort=6678, mac='00:00:00:00:00:06' )
    s7 = net.addSwitch( 's7', protocols='OpenFlow10',
listenPort=6679, mac='00:00:00:00:00:07' )
    s8 = net.addSwitch( 's8', protocols='OpenFlow10',
listenPort=66710, mac='00:00:00:00:00:08' )
    s9 = net.addSwitch( 's9', protocols='OpenFlow10',
listenPort=66711, mac='00:00:00:00:00:09' )
    s10 = net.addSwitch( 's10', protocols='OpenFlow10',
listenPort=66712, mac='00:00:00:00:00:10' )
    s11 = net.addSwitch( 's11', protocols='OpenFlow10',
listenPort=66713, mac='00:00:00:00:00:11' )
    s12 = net.addSwitch( 's12', protocols='OpenFlow10',
listenPort=66714, mac='00:00:00:00:00:12' )
    s13 = net.addSwitch( 's13', protocols='OpenFlow10',
listenPort=66715, mac='00:00:00:00:00:13' )
    s14 = net.addSwitch( 's14', protocols='OpenFlow10',
listenPort=66716, mac='00:00:00:00:00:14' )
    s15 = net.addSwitch( 's15', protocols='OpenFlow10',
listenPort=66717, mac='00:00:00:00:00:15' )
    s16 = net.addSwitch( 's16', protocols='OpenFlow10',
listenPort=66718, mac='00:00:00:00:00:16' )
    s17 = net.addSwitch( 's17', protocols='OpenFlow10',
listenPort=66719, mac='00:00:00:00:00:17' )
    s18 = net.addSwitch( 's18', protocols='OpenFlow10',
listenPort=66720, mac='00:00:00:00:00:18' )
    s19 = net.addSwitch( 's19', protocols='OpenFlow10',
listenPort=66721, mac='00:00:00:00:00:19' )
    s20 = net.addSwitch( 's20', protocols='OpenFlow10',
listenPort=66722, mac='00:00:00:00:00:20' )
    s21 = net.addSwitch( 's21', protocols='OpenFlow10',
listenPort=66723, mac='00:00:00:00:00:21' )
    s22 = net.addSwitch( 's22', protocols='OpenFlow10',
listenPort=66724, mac='00:00:00:00:00:22' )
    s23 = net.addSwitch( 's23', protocols='OpenFlow10',
listenPort=66725, mac='00:00:00:00:00:23' )
    s24 = net.addSwitch( 's24', protocols='OpenFlow10',
listenPort=66726, mac='00:00:00:00:00:24' )
    h25 = net.addHost( 'h25', mac='00:00:00:00:00:25',
ip='10.0.0.25/8' )
    h26 = net.addHost( 'h26', mac='00:00:00:00:00:26',
ip='10.0.0.26/8' )
    h27 = net.addHost( 'h27', mac='00:00:00:00:00:27',
ip='10.0.0.27/8' )
    h28 = net.addHost( 'h28', mac='00:00:00:00:00:28',
ip='10.0.0.28/8' )
    h29 = net.addHost( 'h29', mac='00:00:00:00:00:29',
ip='10.0.0.29/8' )
    h30 = net.addHost( 'h30', mac='00:00:00:00:00:30',
ip='10.0.0.30/8' )
```

```
    h31 = net.addHost( 'h31', mac='00:00:00:00:00:31',
ip='10.0.0.31/8' )
    h32 = net.addHost( 'h32', mac='00:00:00:00:00:32',
ip='10.0.0.32/8' )
    h42 = net.addHost( 'h42', mac='00:00:00:00:00:42',
ip='10.0.0.42/8' )
    h43 = net.addHost( 'h43', mac='00:00:00:00:00:43',
ip='10.0.0.43/8' )
    h44 = net.addHost( 'h44', mac='00:00:00:00:00:44',
ip='10.0.0.44/8' )
    h45 = net.addHost( 'h45', mac='00:00:00:00:00:45',
ip='10.0.0.45/8' )
    h46 = net.addHost( 'h46', mac='00:00:00:00:00:46',
ip='10.0.0.46/8' )
    h47 = net.addHost( 'h47', mac='00:00:00:00:00:47',
ip='10.0.0.47/8' )
    h48 = net.addHost( 'h48', mac='00:00:00:00:00:48',
ip='10.0.0.48/8' )
    h49 = net.addHost( 'h49', mac='00:00:00:00:00:49',
ip='10.0.0.49/8' )
    h50 = net.addHost( 'h50', mac='00:00:00:00:00:50',
ip='10.0.0.50/8' )
    h51 = net.addHost( 'h51', mac='00:00:00:00:00:51',
ip='10.0.0.51/8' )
    h52 = net.addHost( 'h52', mac='00:00:00:00:00:52',
ip='10.0.0.52/8' )
    h53 = net.addHost( 'h53', mac='00:00:00:00:00:53',
ip='10.0.0.53/8' )
    h54 = net.addHost( 'h54', mac='00:00:00:00:00:54',
ip='10.0.0.54/8' )
    h55 = net.addHost( 'h55', mac='00:00:00:00:00:55',
ip='10.0.0.55/8' )
    h56 = net.addHost( 'h56', mac='00:00:00:00:00:56',
ip='10.0.0.56/8' )
    h57 = net.addHost( 'h57', mac='00:00:00:00:00:57',
ip='10.0.0.57/8' )
    h58 = net.addHost( 'h58', mac='00:00:00:00:00:58',
ip='10.0.0.58/8' )
    h59 = net.addHost( 'h59', mac='00:00:00:00:00:59',
ip='10.0.0.59/8' )
    h60 = net.addHost( 'h60', mac='00:00:00:00:00:60',
ip='10.0.0.60/8' )
    h61 = net.addHost( 'h61', mac='00:00:00:00:00:61',
ip='10.0.0.61/8' )
    h62 = net.addHost( 'h62', mac='00:00:00:00:00:62',
ip='10.0.0.62/8' )
    h63 = net.addHost( 'h63', mac='00:00:00:00:00:63',
ip='10.0.0.63/8' )
    h64 = net.addHost( 'h64', mac='00:00:00:00:00:64',
ip='10.0.0.64/8' )
    h65 = net.addHost( 'h65', mac='00:00:00:00:00:65',
ip='10.0.0.65/8' )
    h66 = net.addHost( 'h66', mac='00:00:00:00:00:66',
ip='10.0.0.66/8' )
```

```
    h67 = net.addHost( 'h67', mac='00:00:00:00:00:67',
ip='10.0.0.67/8' )
    h68 = net.addHost( 'h68', mac='00:00:00:00:00:68',
ip='10.0.0.68/8' )
    h69 = net.addHost( 'h69', mac='00:00:00:00:00:69',
ip='10.0.0.69/8' )
    h70 = net.addHost( 'h70', mac='00:00:00:00:00:70',
ip='10.0.0.70/8' )
    h71 = net.addHost( 'h71', mac='00:00:00:00:00:71',
ip='10.0.0.71/8' )
    h72 = net.addHost( 'h72', mac='00:00:00:00:00:72',
ip='10.0.0.72/8' )
    h73 = net.addHost( 'h73', mac='00:00:00:00:00:73',
ip='10.0.0.73/8' )
    h74 = net.addHost( 'h74', mac='00:00:00:00:00:74',
ip='10.0.0.74/8' )
    h75 = net.addHost( 'h75', mac='00:00:00:00:00:75',
ip='10.0.0.75/8' )
    h76 = net.addHost( 'h76', mac='00:00:00:00:00:76',
ip='10.0.0.76/8' )
    h77 = net.addHost( 'h77', mac='00:00:00:00:00:77',
ip='10.0.0.77/8' )
    h78 = net.addHost( 'h78', mac='00:00:00:00:00:78',
ip='10.0.0.78/8' )
    h79 = net.addHost( 'h79', mac='00:00:00:00:00:79',
ip='10.0.0.79/8' )
    h80 = net.addHost( 'h80', mac='00:00:00:00:00:80',
ip='10.0.0.80/8' )
    h81 = net.addHost( 'h81', mac='00:00:00:00:00:81',
ip='10.0.0.81/8' )
    h82 = net.addHost( 'h82', mac='00:00:00:00:00:82',
ip='10.0.0.82/8' )
    h83 = net.addHost( 'h83', mac='00:00:00:00:00:83',
ip='10.0.0.83/8' )
    h84 = net.addHost( 'h84', mac='00:00:00:00:00:84',
ip='10.0.0.84/8' )
    h85 = net.addHost( 'h85', mac='00:00:00:00:00:85',
ip='10.0.0.85/8' )
    h86 = net.addHost( 'h86', mac='00:00:00:00:00:86',
ip='10.0.0.86/8' )
    h87 = net.addHost( 'h87', mac='00:00:00:00:00:87',
ip='10.0.0.87/8' )
    h88 = net.addHost( 'h88', mac='00:00:00:00:00:88',
ip='10.0.0.88/8' )
    h89 = net.addHost( 'h89', mac='00:00:00:00:00:89',
ip='10.0.0.89/8' )
    h90 = net.addHost( 'h90', mac='00:00:00:00:00:90',
ip='10.0.0.90/8' )
    h91 = net.addHost( 'h91', mac='00:00:00:00:00:91',
ip='10.0.0.91/8' )
    h92 = net.addHost( 'h92', mac='00:00:00:00:00:92',
ip='10.0.0.92/8' )
    h93 = net.addHost( 'h93', mac='00:00:00:00:00:93',
ip='10.0.0.93/8' )
```

```
    h94 = net.addHost( 'h94', mac='00:00:00:00:00:94',
ip='10.0.0.94/8' )
    h95 = net.addHost( 'h95', mac='00:00:00:00:00:95',
ip='10.0.0.95/8' )
    h96 = net.addHost( 'h96', mac='00:00:00:00:00:96',
ip='10.0.0.96/8' )
    h97 = net.addHost( 'h97', mac='00:00:00:00:00:97',
ip='10.0.0.97/8' )
    h98 = net.addHost( 'h98', mac='00:00:00:00:00:98',
ip='10.0.0.98/8' )
    h99 = net.addHost( 'h99', mac='00:00:00:00:00:99',
ip='10.0.0.99/8' )
    h10 = net.addHost( 'h10', mac='00:00:00:00:00:10',
ip='10.0.0.10/8' )
    h10 = net.addHost( 'h10', mac='00:00:00:00:00:10',
ip='10.0.0.10/8' )
    h10 = net.addHost( 'h10', mac='00:00:00:00:00:10',
ip='10.0.0.10/8' )
    h10 = net.addHost( 'h10', mac='00:00:00:00:00:10',
ip='10.0.0.10/8' )
    h10 = net.addHost( 'h10', mac='00:00:00:00:00:10',
ip='10.0.0.10/8' )
    h10 = net.addHost( 'h10', mac='00:00:00:00:00:10',
ip='10.0.0.10/8' )
    h10 = net.addHost( 'h10', mac='00:00:00:00:00:10',
ip='10.0.0.10/8' )
    h10 = net.addHost( 'h10', mac='00:00:00:00:00:10',
ip='10.0.0.10/8' )
    h10 = net.addHost( 'h10', mac='00:00:00:00:00:10',
ip='10.0.0.10/8' )
    h10 = net.addHost( 'h10', mac='00:00:00:00:00:10',
ip='10.0.0.10/8' )
    h11 = net.addHost( 'h11', mac='00:00:00:00:00:11',
ip='10.0.0.11/8' )
    h11 = net.addHost( 'h11', mac='00:00:00:00:00:11',
ip='10.0.0.11/8' )
    h11 = net.addHost( 'h11', mac='00:00:00:00:00:11',
ip='10.0.0.11/8' )
    h11 = net.addHost( 'h11', mac='00:00:00:00:00:11',
ip='10.0.0.11/8' )
    c30 = net.addController( 'c30' )

    print "*** Creating links"
    net.addLink(s17, h11)
    net.addLink(s17, h11)
    net.addLink(s17, h11)
    net.addLink(s17, h11)
    net.addLink(s17, h10)
    net.addLink(s17, h10)
    net.addLink(s17, h10)
    net.addLink(s17, h10)
    net.addLink(h10, s16)
    net.addLink(h10, s16)
    net.addLink(h10, s16)
    net.addLink(h10, s16)
```

```
net.addLink(h99, s16)
net.addLink(h98, s16)
net.addLink(h10, s16)
net.addLink(h10, s16)
net.addLink(s16, s17)
net.addLink(s15, s17)
net.addLink(s15, s16)
net.addLink(s14, s17)
net.addLink(s14, s16)
net.addLink(s14, s15)
net.addLink(s13, s15)
net.addLink(s13, s14)
net.addLink(s12, s15)
net.addLink(s12, s14)
net.addLink(s11, s15)
net.addLink(s11, s14)
net.addLink(s12, s13)
net.addLink(s11, s12)
net.addLink(s10, s13)
net.addLink(s10, s12)
net.addLink(s10, s11)
net.addLink(s9, s13)
net.addLink(s9, s12)
net.addLink(s9, s11)
net.addLink(s8, s13)
net.addLink(s8, s12)
net.addLink(s8, s11)
net.addLink(s7, s13)
net.addLink(s7, s12)
net.addLink(s7, s11)
net.addLink(s6, s13)
net.addLink(s6, s12)
net.addLink(s6, s11)
net.addLink(s5, s13)
net.addLink(s5, s12)
net.addLink(s5, s11)
net.addLink(s4, s13)
net.addLink(s4, s12)
net.addLink(s4, s11)
net.addLink(s3, s13)
net.addLink(s3, s12)
net.addLink(s3, s11)
net.addLink(s2, s13)
net.addLink(s2, s12)
net.addLink(s2, s11)
net.addLink(s1, s13)
net.addLink(s1, s12)
net.addLink(s1, s11)
net.addLink(s16, s17)
net.addLink(s16, s17)
net.addLink(s24, s17)
net.addLink(s24, s16)
net.addLink(s23, s17)
net.addLink(s23, s16)
net.addLink(s23, s24)
```

```
net.addLink(s22, s24)
net.addLink(s22, s23)
net.addLink(s21, s24)
net.addLink(s21, s23)
net.addLink(s21, s22)
net.addLink(s20, s22)
net.addLink(s20, s21)
net.addLink(s19, s22)
net.addLink(s19, s21)
net.addLink(s18, s22)
net.addLink(s18, s21)
net.addLink(h97, s20)
net.addLink(h96, s20)
net.addLink(h95, s20)
net.addLink(h94, s20)
net.addLink(h93, s20)
net.addLink(h92, s20)
net.addLink(h91, s20)
net.addLink(h90, s20)
net.addLink(h89, s19)
net.addLink(h88, s19)
net.addLink(h87, s19)
net.addLink(h86, s19)
net.addLink(h85, s19)
net.addLink(h84, s19)
net.addLink(h83, s19)
net.addLink(h82, s19)
net.addLink(h81, s18)
net.addLink(h80, s18)
net.addLink(h79, s18)
net.addLink(h78, s18)
net.addLink(h77, s18)
net.addLink(h76, s18)
net.addLink(h75, s18)
net.addLink(h74, s18)
net.addLink(h73, s10)
net.addLink(h72, s10)
net.addLink(h71, s10)
net.addLink(h70, s10)
net.addLink(h69, s10)
net.addLink(h68, s10)
net.addLink(h67, s10)
net.addLink(h66, s10)
net.addLink(h73, s9)
net.addLink(h72, s9)
net.addLink(h71, s9)
net.addLink(h70, s9)
net.addLink(h69, s9)
net.addLink(h68, s9)
net.addLink(h67, s9)
net.addLink(h66, s9)
net.addLink(h65, s8)
net.addLink(h64, s8)
net.addLink(h63, s8)
net.addLink(h62, s8)
```

```
net.addLink(h61, s8)
net.addLink(h60, s8)
net.addLink(h59, s8)
net.addLink(h58, s8)
net.addLink(h65, s7)
net.addLink(h64, s7)
net.addLink(h63, s7)
net.addLink(h62, s7)
net.addLink(h61, s7)
net.addLink(h60, s7)
net.addLink(h59, s7)
net.addLink(h58, s7)
net.addLink(h57, s6)
net.addLink(h56, s6)
net.addLink(h55, s6)
net.addLink(h54, s6)
net.addLink(h53, s6)
net.addLink(h52, s6)
net.addLink(h51, s6)
net.addLink(h50, s6)
net.addLink(h57, s5)
net.addLink(h56, s5)
net.addLink(h55, s5)
net.addLink(h54, s5)
net.addLink(h53, s5)
net.addLink(h52, s5)
net.addLink(h51, s5)
net.addLink(h50, s5)
net.addLink(h49, s4)
net.addLink(h48, s4)
net.addLink(h47, s4)
net.addLink(h46, s4)
net.addLink(h45, s4)
net.addLink(h44, s4)
net.addLink(s4, h43)
net.addLink(h42, s4)
net.addLink(h32, s2)
net.addLink(h31, s2)
net.addLink(h30, s2)
net.addLink(h29, s2)
net.addLink(h28, s2)
net.addLink(h27, s2)
net.addLink(h26, s2)
net.addLink(h25, s2)
net.addLink(h49, s3)
net.addLink(h48, s3)
net.addLink(h47, s3)
net.addLink(h46, s3)
net.addLink(h45, s3)
net.addLink(h44, s3)
net.addLink(h43, s3)
net.addLink(h42, s3)
net.addLink(h32, s1)
net.addLink(h31, s1)
net.addLink(h30, s1)
```

```
    net.addLink(h29, s1)
    net.addLink(h28, s1)
    net.addLink(h27, s1)
    net.addLink(h26, s1)
    net.addLink(h25, s1)

    print "*** Starting network"
    net.build()
    c30.start()

    print "*** Running CLI"
    CLI( net )

    print "*** Stopping network"
    net.stop()

if __name__ == '__main__':
    setLogLevel( 'info' )
    topology()
```

4.3 Campus Network Topology – Profiling Overead Computation (Chapter 8)

```
#!/usr/bin/python

"""
Script created by VND - Visual Network Description (SDN version)
"""
from mininet.net import Mininet
from mininet.node import Controller, RemoteController,
OVSKernelSwitch, IVSSwitch, UserSwitch
from mininet.link import Link, TCLink
from mininet.cli import CLI
from mininet.log import setLogLevel

def topology():

    "Create a network."
    net = Mininet( controller=RemoteController, link=TCLink,
switch=OVSKernelSwitch )

    print "*** Creating nodes"
    s1 = net.addSwitch( 's1', listenPort=6673,
mac='00:00:00:00:00:01' )
    h2 = net.addHost( 'h2', mac='00:00:00:00:00:02',
ip='10.0.0.2/8' )
    h3 = net.addHost( 'h3', mac='00:00:00:00:00:03',
ip='10.0.0.3/8' )
    h4 = net.addHost( 'h4', mac='00:00:00:00:00:04',
ip='10.0.0.4/8' )
    h5 = net.addHost( 'h5', mac='00:00:00:00:00:05',
ip='10.0.0.5/8' )
    h6 = net.addHost( 'h6', mac='00:00:00:00:00:06',
ip='10.0.0.6/8' )
```

```
    h7 = net.addHost( 'h7', mac='00:00:00:00:00:07',
ip='10.0.0.7/8' )
    h8 = net.addHost( 'h8', mac='00:00:00:00:00:08',
ip='10.0.0.8/8' )
    h9 = net.addHost( 'h9', mac='00:00:00:00:00:09',
ip='10.0.0.9/8' )
    h10 = net.addHost( 'h10', mac='00:00:00:00:00:10',
ip='10.0.0.10/8' )
    h11 = net.addHost( 'h11', mac='00:00:00:00:00:11',
ip='10.0.0.11/8' )
    h12 = net.addHost( 'h12', mac='00:00:00:00:00:12',
ip='10.0.0.12/8' )
    h13 = net.addHost( 'h13', mac='00:00:00:00:00:13',
ip='10.0.0.13/8' )
    c26 = net.addController( 'c26' )

    print "*** Creating links"
    net.addLink(s1, h13)
    net.addLink(s1, h12)
    net.addLink(s1, h11)
    net.addLink(s1, h10)
    net.addLink(s1, h9)
    net.addLink(s1, h8)
    net.addLink(h7, s1)
    net.addLink(h6, s1)
    net.addLink(h5, s1)
    net.addLink(h4, s1)
    net.addLink(h3, s1)
    net.addLink(h2, s1)

    print "*** Starting network"
    net.start()
    c26.start()

    print "*** Running CLI"
    CLI( net )

    print "*** Stopping network"
    net.stop()

if __name__ == '__main__':
    setLogLevel( 'info' )
    topology()
```

APPENDIX – 5

5. RYU Control Scripts

5.1 Switching Application (with QoS support)

5.2 RESTful Flow Configuration Support Module

5.3 SwitchPort Monitoring and Queue Calculator Constructs

5.4 DC Traffic Monitor and Route Installer

5.5 OpenFlow Traffic Measurement

5.1 Switching Application (with QoS support)

```
from ryu.base import app_manager
from ryu.controller import ofp_event
from ryu.controller.handler import CONFIG_DISPATCHER,
MAIN_DISPATCHER
from ryu.controller.handler import set_ev_cls
from ryu.ofproto import ofproto_v1_3
from ryu.lib.packet import packet
from ryu.lib.packet import ethernet
from ryu.lib.packet import ether_types
from ryu.lib import pcaplib


class SimpleSwitch13(app_manager.RyuApp):
    OFP_VERSIONS = [ofproto_v1_3.OFP_VERSION]

    def __init__(self, *args, **kwargs):
        super(SimpleSwitch13, self).__init__(*args, **kwargs)
        self.mac_to_port = {}
        self.pcap_pen = pcaplib.Writer(open('mypcap.pcap', 'wb'))
        # Creating an instance with a PCAP filename

    @set_ev_cls(ofp_event.EventOFPSwitchFeatures,  CONFIG_DISPATCHER)
    def switch_features_handler(self, ev):
        datapath = ev.msg.datapath
        ofproto = datapath.ofproto
        parser = datapath.ofproto_parser

        # install table-miss flow entry
        #
        # We specify NO BUFFER to max_len of the output action due
to
        # OVS bug. At this moment, if we specify a lesser number,
e.g.,
        # 128, OVS will send Packet-In with invalid buffer_id and
        # truncated packet data. In that case, we cannot output
packets
        # correctly.  The bug has been fixed in OVS v2.1.0.
        match = parser.OFPMatch()
        actions = [parser.OFPActionOutput(ofproto.OFPP_CONTROLLER,
                                          ofproto.OFPCML_NO_BUFFER)]
        self.add_flow(datapath, 0, match, actions)

    def add_flow(self, datapath, priority, match, actions,
buffer_id=None):
        ofproto = datapath.ofproto
        parser = datapath.ofproto_parser

        inst =
[parser.OFPInstructionActions(ofproto.OFPIT_APPLY_ACTIONS,
                                             actions)]
        if buffer_id:
```

```
            mod = parser.OFPFlowMod(datapath=datapath,
buffer_id=buffer_id,
                                    priority=priority, match=match,
                                    instructions=inst, table_id=1)
        else:
            mod = parser.OFPFlowMod(datapath=datapath,
priority=priority,
                                    match=match, instructions=inst,
table_id=1)
        datapath.send_msg(mod)

    @set_ev_cls(ofp_event.EventOFPPacketIn, MAIN_DISPATCHER)
    def _packet_in_handler(self, ev):
        # If you hit this you might want to increase
        # the "miss_send_length" of your switch
        if ev.msg.msg_len < ev.msg.total_len:
            self.logger.debug("packet truncated: only %s of %s
bytes",
                              ev.msg.msg_len, ev.msg.total_len)
        msg = ev.msg
        self.pcap_pen.write_pkt(msg.data)
        datapath = msg.datapath
        ofproto = datapath.ofproto
        parser = datapath.ofproto_parser
        in_port = msg.match['in_port']

        pkt = packet.Packet(msg.data)
        eth = pkt.get_protocols(ethernet.ethernet)[0]

        if eth.ethertype == ether_types.ETH_TYPE_LLDP:
            # ignore lldp packet
            return
        dst = eth.dst
        src = eth.src

        dpid = datapath.id
        self.mac_to_port.setdefault(dpid, {})

        self.logger.info("packet in %s %s %s %s", dpid, src, dst,
in_port)

        # learn a mac address to avoid FLOOD next time.
        self.mac_to_port[dpid][src] = in_port

        if dst in self.mac_to_port[dpid]:
            out_port = self.mac_to_port[dpid][dst]
        else:
            out_port = ofproto.OFPP_FLOOD

        actions = [parser.OFPActionOutput(out_port)]

        # install a flow to avoid packet_in next time
        if out_port != ofproto.OFPP_FLOOD:
            match = parser.OFPMatch(in_port=in_port, eth_dst=dst)
```

```
            # verify if we have a valid buffer_id, if yes avoid to
send both
            # flow_mod & packet_out
            if msg.buffer_id != ofproto.OFP_NO_BUFFER:
                self.add_flow(datapath, 1, match, actions,
msg.buffer_id)
                return
            else:
                self.add_flow(datapath, 1, match, actions)
        data = None
        if msg.buffer_id == ofproto.OFP_NO_BUFFER:
            data = msg.data

        out = parser.OFPPacketOut(datapath=datapath,
buffer_id=msg.buffer_id,
                                  in_port=in_port, actions=actions,
data=data)
        datapath.send_msg(out)
```

5.2 RESTful Flow Configuration Support Module

```
import logging
import json
import re

from webob import Response

from ryu.app import conf_switch_key as cs_key
from ryu.app.wsgi import ControllerBase, WSGIApplication, route
from ryu.base import app_manager
from ryu.controller import conf_switch
from ryu.controller import ofp_event
from ryu.controller import dpset
from ryu.controller.handler import set_ev_cls
from ryu.controller.handler import MAIN_DISPATCHER
from ryu.exception import OFPUnknownVersion
from ryu.lib import dpid as dpid_lib
from ryu.lib import mac
from ryu.lib import ofctl_v1_0
from ryu.lib import ofctl_v1_2
from ryu.lib import ofctl_v1_3
from ryu.lib.ovs import bridge
from ryu.ofproto import ofproto_v1_0
from ryu.ofproto import ofproto_v1_2
from ryu.ofproto import ofproto_v1_3
from ryu.ofproto import ofproto_v1_3_parser
from ryu.ofproto import ether
from ryu.ofproto import inet


# ==============================
#          REST API
# ==============================
#
```

```
#  Note: specify switch and vlan group, as follows.
#   {switch-id} : 'all' or switchID
#   {vlan-id}   : 'all' or vlanID
#
# about queue status
#
# get status of queue
# GET /qos/queue/status/{switch-id}
#
# about queues
# get a queue configurations
# GET /qos/queue/{switch-id}
#
# set a queue to the switches
# POST /qos/queue/{switch-id}
#
# request body format:
#  {"port_name":"<name of port>",
#   "type": "<linux-htb or linux-other>",
#   "max-rate": "<int>",
#   "queues":[{"max_rate": "<int>", "min_rate": "<int>"},...]}
#
#   Note: This operation override
#         previous configurations.
#   Note: Queue configurations are available for
#         OpenvSwitch.
#   Note: port_name is optional argument.
#         If does not pass the port_name argument,
#         all ports are target for configuration.
#
# delete queue
# DELETE /qos/queue/{swtich-id}
#
#   Note: This operation delete relation of qos record from
#         qos colum in Port table. Therefore,
#         QoS records and Queue records will remain.
#
# about qos rules
#
# get rules of qos
# * for no vlan
# GET /qos/rules/{switch-id}
#
# * for specific vlan group
# GET /qos/rules/{switch-id}/{vlan-id}
#
# set a qos rules
#
#   QoS rules will do the processing pipeline,
#   which entries are register the first table (by default table id
0)
#   and process will apply and go to next table.
#
# * for no vlan
# POST /qos/{switch-id}
```

```
#
# * for specific vlan group
# POST /qos/{switch-id}/{vlan-id}
#
#  request body format:
#   {"priority": "<value>",
#    "match": {"<field1>": "<value1>", "<field2>": "<value2>",...},
#    "actions": {"<action1>": "<value1>", "<action2>":
"<value2>",...}
#   }
#
#  Description
#    * priority field
#     <value>
#    "0 to 65533"
#
#   Note: When "priority" has not been set up,
#         "priority: 1" is set to "priority".
#
#    * match field
#     <field> : <value>
#    "in_port" : "<int>"
#    "dl_src"  : "<xx:xx:xx:xx:xx:xx>"
#    "dl_dst"  : "<xx:xx:xx:xx:xx:xx>"
#    "dl_type" : "<ARP or IPv4 or IPv6>"
#    "nw_src"  : "<A.B.C.D/M>"
#    "nw_dst"  : "<A.B.C.D/M>"
#    "ipv6_src": "<xxxx:xxxx:xxxx:xxxx:xxxx:xxxx:xxxx:xxxx/M>"
#    "ipv6_dst": "<xxxx:xxxx:xxxx:xxxx:xxxx:xxxx:xxxx:xxxx/M>"
#    "nw_proto": "<TCP or UDP or ICMP or ICMPv6>"
#    "tp_src"  : "<int>"
#    "tp_dst"  : "<int>"
#    "ip_dscp" : "<int>"
#
#    * actions field
#     <field> : <value>
#    "mark": <dscp-value>
#    sets the IPv4 ToS/DSCP field to tos.
#    "meter": <meter-id>
#    apply meter entry
#    "queue": <queue-id>
#    register queue specified by queue-id
#
#   Note: When "actions" has not been set up,
#         "queue: 0" is set to "actions".
#
# delete a qos rules
# * for no vlan
# DELETE /qos/rule/{switch-id}
#
# * for specific vlan group
# DELETE /qos/{switch-id}/{vlan-id}
#
#  request body format:
#   {"<field>":"<value>"}
```

```
#
#     <field>  : <value>
#    "qos_id" : "<int>" or "all"
#
# about meter entries
#
# set a meter entry
# POST /qos/meter/{switch-id}
#
#  request body format:
#   {"meter_id": <int>,
#    "bands":[{"action": "<DROP or DSCP_REMARK>",
#              "flag": "<KBPS or PKTPS or BURST or STATS"
#              "burst_size": <int>,
#              "rate": <int>,
#              "prec_level": <int>},...]}
#
# delete a meter entry
# DELETE /qos/meter/{switch-id}
#
#  request body format:
#   {"<field>":"<value>"}
#
#     <field>  : <value>
#    "meter_id" : "<int>"
#


SWITCHID_PATTERN = dpid_lib.DPID_PATTERN + r'|all'
VLANID_PATTERN = r'[0-9]{1,4}|all'

QOS_TABLE_ID = 0

REST_ALL = 'all'
REST_SWITCHID = 'switch_id'
REST_COMMAND_RESULT = 'command_result'
REST_PRIORITY = 'priority'
REST_VLANID = 'vlan_id'
REST_PORT_NAME = 'port_name'
REST_QUEUE_TYPE = 'type'
REST_QUEUE_MAX_RATE = 'max_rate'
REST_QUEUE_MIN_RATE = 'min_rate'
REST_QUEUES = 'queues'
REST_QOS = 'qos'
REST_QOS_ID = 'qos_id'
REST_COOKIE = 'cookie'

REST_MATCH = 'match'
REST_IN_PORT = 'in_port'
REST_SRC_MAC = 'dl_src'
REST_DST_MAC = 'dl_dst'
REST_DL_TYPE = 'dl_type'
REST_DL_TYPE_ARP = 'ARP'
REST_DL_TYPE_IPV4 = 'IPv4'
REST_DL_TYPE_IPV6 = 'IPv6'
```

```
REST_DL_VLAN = 'dl_vlan'
REST_SRC_IP = 'nw_src'
REST_DST_IP = 'nw_dst'
REST_SRC_IPV6 = 'ipv6_src'
REST_DST_IPV6 = 'ipv6_dst'
REST_NW_PROTO = 'nw_proto'
REST_NW_PROTO_TCP = 'TCP'
REST_NW_PROTO_UDP = 'UDP'
REST_NW_PROTO_ICMP = 'ICMP'
REST_NW_PROTO_ICMPV6 = 'ICMPv6'
REST_TP_SRC = 'tp_src'
REST_TP_DST = 'tp_dst'
REST_DSCP = 'ip_dscp'

REST_ACTION = 'actions'
REST_ACTION_QUEUE = 'queue'
REST_ACTION_MARK = 'mark'
REST_ACTION_METER = 'meter'

REST_METER_ID = 'meter_id'
REST_METER_BURST_SIZE = 'burst_size'
REST_METER_RATE = 'rate'
REST_METER_PREC_LEVEL = 'prec_level'
REST_METER_BANDS = 'bands'
REST_METER_ACTION_DROP = 'drop'
REST_METER_ACTION_REMARK = 'remark'

DEFAULT_FLOW_PRIORITY = 0
QOS_PRIORITY_MAX = ofproto_v1_3_parser.UINT16_MAX - 1
QOS_PRIORITY_MIN = 1

VLANID_NONE = 0
VLANID_MIN = 2
VLANID_MAX = 4094
COOKIE_SHIFT_VLANID = 32

BASE_URL = '/qos'
REQUIREMENTS = {'switchid': SWITCHID_PATTERN,
                'vlanid': VLANID_PATTERN}

LOG = logging.getLogger(__name__)


class RestQoSAPI(app_manager.RyuApp):

    OFP_VERSIONS = [ofproto_v1_0.OFP_VERSION,
                    ofproto_v1_2.OFP_VERSION,
                    ofproto_v1_3.OFP_VERSION]

    _CONTEXTS = {
        'dpset': dpset.DPSet,
        'conf_switch': conf_switch.ConfSwitchSet,
        'wsgi': WSGIApplication}

    def __init__(self, *args, **kwargs):
```

```
        super(RestQoSAPI, self).__init__(*args, **kwargs)

        # logger configure
        QoSController.set_logger(self.logger)
        self.cs = kwargs['conf_switch']
        self.dpset = kwargs['dpset']
        wsgi = kwargs['wsgi']
        self.waiters = {}
        self.data = {}
        self.data['dpset'] = self.dpset
        self.data['waiters'] = self.waiters
        wsgi.registory['QoSController'] = self.data
        wsgi.register(QoSController, self.data)

    def stats_reply_handler(self, ev):
        msg = ev.msg
        dp = msg.datapath

        if dp.id not in self.waiters:
            return
        if msg.xid not in self.waiters[dp.id]:
            return
        lock, msgs = self.waiters[dp.id][msg.xid]
        msgs.append(msg)

        flags = 0
        if dp.ofproto.OFP_VERSION == ofproto_v1_0.OFP_VERSION or \
                dp.ofproto.OFP_VERSION == ofproto_v1_2.OFP_VERSION:
            flags = dp.ofproto.OFPSF_REPLY_MORE
        elif dp.ofproto.OFP_VERSION == ofproto_v1_3.OFP_VERSION:
            flags = dp.ofproto.OFPMPF_REPLY_MORE

        if msg.flags & flags:
            return
        del self.waiters[dp.id][msg.xid]
        lock.set()

    @set_ev_cls(conf_switch.EventConfSwitchSet)
    def conf_switch_set_handler(self, ev):
        if ev.key == cs_key.OVSDB_ADDR:
            QoSController.set_ovsdb_addr(ev.dpid, ev.value)
        else:
            QoSController._LOGGER.debug("unknown event: %s", ev)

    @set_ev_cls(conf_switch.EventConfSwitchDel)
    def conf_switch_del_handler(self, ev):
        if ev.key == cs_key.OVSDB_ADDR:
            QoSController.delete_ovsdb_addr(ev.dpid)
        else:
            QoSController._LOGGER.debug("unknown event: %s", ev)

    @set_ev_cls(dpset.EventDP, dpset.DPSET_EV_DISPATCHER)
    def handler_datapath(self, ev):
        if ev.enter:
            QoSController.regist_ofs(ev.dp, self.CONF)
```

```
        else:
            QoSController.unregist_ofs(ev.dp)

    # for OpenFlow version1.0
    @set_ev_cls(ofp_event.EventOFPFlowStatsReply, MAIN_DISPATCHER)
    def stats_reply_handler_v1_0(self, ev):
        self.stats_reply_handler(ev)

    # for OpenFlow version1.2 or later
    @set_ev_cls(ofp_event.EventOFPStatsReply, MAIN_DISPATCHER)
    def stats_reply_handler_v1_2(self, ev):
        self.stats_reply_handler(ev)

    # for OpenFlow version1.2 or later
    @set_ev_cls(ofp_event.EventOFPQueueStatsReply, MAIN_DISPATCHER)
    def queue_stats_reply_handler_v1_2(self, ev):
        self.stats_reply_handler(ev)

    # for OpenFlow version1.2 or later
    @set_ev_cls(ofp_event.EventOFPMeterStatsReply, MAIN_DISPATCHER)
    def meter_stats_reply_handler_v1_2(self, ev):
        self.stats_reply_handler(ev)


class QoSOfsList(dict):

    def __init__(self):
        super(QoSOfsList, self).__init__()

    def get_ofs(self, dp_id):
        if len(self) == 0:
            raise ValueError('qos sw is not connected.')

        dps = {}
        if dp_id == REST_ALL:
            dps = self
        else:
            try:
                dpid = dpid_lib.str_to_dpid(dp_id)
            except:
                raise ValueError('Invalid switchID.')

            if dpid in self:
                dps = {dpid: self[dpid]}
            else:
                msg = 'qos sw is not connected. : switchID=%s' %
dp_id
                raise ValueError(msg)

        return dps


class QoSController(ControllerBase):

    _OFS_LIST = QoSOfsList()
```

```
    _LOGGER = None

    def __init__(self, req, link, data, **config):
        super(QoSController, self).__init__(req, link, data,
**config)
        self.dpset = data['dpset']
        self.waiters = data['waiters']

    @classmethod
    def set_logger(cls, logger):
        cls._LOGGER = logger
        cls._LOGGER.propagate = False
        hdlr = logging.StreamHandler()
        fmt_str = '[QoS][%(levelname)s] %(message)s'
        hdlr.setFormatter(logging.Formatter(fmt_str))
        cls._LOGGER.addHandler(hdlr)

    @staticmethod
    def regist_ofs(dp, CONF):
        if dp.id in QoSController._OFS_LIST:
            return

        dpid_str = dpid_lib.dpid_to_str(dp.id)
        try:
            f_ofs = QoS(dp, CONF)
            f_ofs.set_default_flow()
        except OFPUnknownVersion as message:
            QoSController._LOGGER.info('dpid=%s: %s',
                                       dpid_str, message)
            return

        QoSController._OFS_LIST.setdefault(dp.id, f_ofs)
        QoSController._LOGGER.info('dpid=%s: Join qos switch.',
                                   dpid_str)

    @staticmethod
    def unregist_ofs(dp):
        if dp.id in QoSController._OFS_LIST:
            del QoSController._OFS_LIST[dp.id]
            QoSController._LOGGER.info('dpid=%s: Leave qos switch.',
                                       dpid_lib.dpid_to_str(dp.id))

    @staticmethod
    def set_ovsdb_addr(dpid, value):
        ofs = QoSController._OFS_LIST.get(dpid, None)
        if ofs is not None:
            ofs.set_ovsdb_addr(dpid, value)

    @staticmethod
    def delete_ovsdb_addr(dpid):
        ofs = QoSController._OFS_LIST.get(dpid, None)
        ofs.set_ovsdb_addr(dpid, None)

    @route('qos_switch', BASE_URL + '/queue/{switchid}',
           methods=['GET'], requirements=REQUIREMENTS)
```

```
def get_queue(self, req, switchid, **_kwargs):
    return self._access_switch(req, switchid, VLANID_NONE,
                               'get_queue', None)

@route('qos_switch', BASE_URL + '/queue/{switchid}',
       methods=['POST'], requirements=REQUIREMENTS)
def set_queue(self, req, switchid, **_kwargs):
    return self._access_switch(req, switchid, VLANID_NONE,
                               'set_queue', None)

@route('qos_switch', BASE_URL + '/queue/{switchid}',
       methods=['DELETE'], requirements=REQUIREMENTS)
def delete_queue(self, req, switchid, **_kwargs):
    return self._access_switch(req, switchid, VLANID_NONE,
                               'delete_queue', None)

@route('qos_switch', BASE_URL + '/queue/status/{switchid}',
       methods=['GET'], requirements=REQUIREMENTS)
def get_status(self, req, switchid, **_kwargs):
    return self._access_switch(req, switchid, VLANID_NONE,
                               'get_status', self.waiters)

@route('qos_switch', BASE_URL + '/rules/{switchid}',
       methods=['GET'], requirements=REQUIREMENTS)
def get_qos(self, req, switchid, **_kwargs):
    return self._access_switch(req, switchid, VLANID_NONE,
                               'get_qos', self.waiters)

@route('qos_switch', BASE_URL + '/rules/{switchid}/{vlanid}',
       methods=['GET'], requirements=REQUIREMENTS)
def get_vlan_qos(self, req, switchid, vlanid, **_kwargs):
    return self._access_switch(req, switchid, vlanid,
                               'get_qos', self.waiters)

@route('qos_switch', BASE_URL + '/rules/{switchid}',
       methods=['POST'], requirements=REQUIREMENTS)
def set_qos(self, req, switchid, **_kwargs):
    return self._access_switch(req, switchid, VLANID_NONE,
                               'set_qos', self.waiters)

@route('qos_switch', BASE_URL + '/rules/{switchid}/{vlanid}',
       methods=['POST'], requirements=REQUIREMENTS)
def set_vlan_qos(self, req, switchid, vlanid, **_kwargs):
    return self._access_switch(req, switchid, vlanid,
                               'set_qos', self.waiters)

@route('qos_switch', BASE_URL + '/rules/{switchid}',
       methods=['DELETE'], requirements=REQUIREMENTS)
def delete_qos(self, req, switchid, **_kwargs):
    return self._access_switch(req, switchid, VLANID_NONE,
                               'delete_qos', self.waiters)

@route('qos_switch', BASE_URL + '/rules/{switchid}/{vlanid}',
       methods=['DELETE'], requirements=REQUIREMENTS)
def delete_vlan_qos(self, req, switchid, vlanid, **_kwargs):
```

```
        return self._access_switch(req, switchid, vlanid,
                                   'delete_qos', self.waiters)

    @route('qos_switch', BASE_URL + '/meter/{switchid}',
           methods=['GET'], requirements=REQUIREMENTS)
    def get_meter(self, req, switchid, **_kwargs):
        return self._access_switch(req, switchid, VLANID_NONE,
                                   'get_meter', self.waiters)

    @route('qos_switch', BASE_URL + '/meter/{switchid}',
           methods=['POST'], requirements=REQUIREMENTS)
    def set_meter(self, req, switchid, **_kwargs):
        return self._access_switch(req, switchid, VLANID_NONE,
                                   'set_meter', self.waiters)

    @route('qos_switch', BASE_URL + '/meter/{switchid}',
           methods=['DELETE'], requirements=REQUIREMENTS)
    def delete_meter(self, req, switchid, **_kwargs):
        return self._access_switch(req, switchid, VLANID_NONE,
                                   'delete_meter', self.waiters)

    def _access_switch(self, req, switchid, vlan_id, func, waiters):
        try:
            rest = json.loads(req.body) if req.body else {}
        except SyntaxError:
            QoSController._LOGGER.debug('invalid syntax %s',
req.body)
            return Response(status=400)

        try:
            dps = self._OFS_LIST.get_ofs(switchid)
            vid = QoSController._conv_toint_vlanid(vlan_id)
        except ValueError as message:
            return Response(status=400, body=str(message))

        msgs = []
        for f_ofs in dps.values():
            function = getattr(f_ofs, func)
            try:
                if waiters is not None:
                    msg = function(rest, vid, waiters)
                else:
                    msg = function(rest, vid)
            except ValueError as message:
                return Response(status=400, body=str(message))
            msgs.append(msg)

        body = json.dumps(msgs)
        return Response(content_type='application/json', body=body)

    @staticmethod
    def _conv_toint_vlanid(vlan_id):
        if vlan_id != REST_ALL:
            vlan_id = int(vlan_id)
            if (vlan_id != VLANID_NONE and
```

```
                    (vlan_id < VLANID_MIN or VLANID_MAX < vlan_id)):
                msg = 'Invalid {vlan_id} value. Set [%d-%d]' %
(VLANID_MIN,

VLANID_MAX)
                raise ValueError(msg)
        return vlan_id


class QoS(object):

    _OFCTL = {ofproto_v1_0.OFP_VERSION: ofctl_v1_0,
              ofproto_v1_2.OFP_VERSION: ofctl_v1_2,
              ofproto_v1_3.OFP_VERSION: ofctl_v1_3}

    def __init__(self, dp, CONF):
        super(QoS, self).__init__()
        self.vlan_list = {}
        self.vlan_list[VLANID_NONE] = 0  # for VLAN=None
        self.dp = dp
        self.version = dp.ofproto.OFP_VERSION
        self.queue_list = {}
        self.CONF = CONF
        self.ovsdb_addr = None
        self.ovs_bridge = None

        if self.version not in self._OFCTL:
            raise OFPUnknownVersion(version=self.version)

        self.ofctl = self._OFCTL[self.version]

    def set_default_flow(self):
        if self.version == ofproto_v1_0.OFP_VERSION:
            return

        cookie = 0
        priority = DEFAULT_FLOW_PRIORITY
        actions = [{'type': 'GOTO_TABLE',
                    'table_id': QOS_TABLE_ID + 1}]
        flow = self._to_of_flow(cookie=cookie,
                                priority=priority,
                                match={},
                                actions=actions)

        cmd = self.dp.ofproto.OFPFC_ADD
        self.ofctl.mod_flow_entry(self.dp, flow, cmd)

    def set_ovsdb_addr(self, dpid, ovsdb_addr):
        # easy check if the address format valid
        _proto, _host, _port = ovsdb_addr.split(':')

        old_address = self.ovsdb_addr
        if old_address == ovsdb_addr:
            return
        if ovsdb_addr is None:
```

```
            if self.ovs_bridge:
                self.ovs_bridge.del_controller()
                self.ovs_bridge = None
            return
        self.ovsdb_addr = ovsdb_addr
        if self.ovs_bridge is None:
            ovs_bridge = bridge.OVSBridge(self.CONF, dpid,
ovsdb_addr)
            self.ovs_bridge = ovs_bridge
            try:
                ovs_bridge.init()
            except:
                raise ValueError('ovsdb addr is not available.')

    def _update_vlan_list(self, vlan_list):
        for vlan_id in self.vlan_list.keys():
            if vlan_id is not VLANID_NONE and vlan_id not in
vlan_list:
                del self.vlan_list[vlan_id]

    def _get_cookie(self, vlan_id):
        if vlan_id == REST_ALL:
            vlan_ids = self.vlan_list.keys()
        else:
            vlan_ids = [vlan_id]

        cookie_list = []
        for vlan_id in vlan_ids:
            self.vlan_list.setdefault(vlan_id, 0)
            self.vlan_list[vlan_id] += 1
            self.vlan_list[vlan_id] &=
ofproto_v1_3_parser.UINT32_MAX
            cookie = (vlan_id << COOKIE_SHIFT_VLANID) + \
                self.vlan_list[vlan_id]
            cookie_list.append([cookie, vlan_id])

        return cookie_list

    @staticmethod
    def _cookie_to_qosid(cookie):
        return cookie & ofproto_v1_3_parser.UINT32_MAX

    # REST command template
    def rest_command(func):
        def _rest_command(*args, **kwargs):
            key, value = func(*args, **kwargs)
            switch_id = dpid_lib.dpid_to_str(args[0].dp.id)
            return {REST_SWITCHID: switch_id,
                    key: value}
        return _rest_command

    @rest_command
    def get_status(self, req, vlan_id, waiters):
        if self.version == ofproto_v1_0.OFP_VERSION:
```

```
            raise ValueError('get_status operation is not
supported')

        msgs = self.ofctl.get_queue_stats(self.dp, waiters)
        return REST_COMMAND_RESULT, msgs

    @rest_command
    def get_queue(self, rest, vlan_id):
        if len(self.queue_list):
            msg = {'result': 'success',
                   'details': self.queue_list}
        else:
            msg = {'result': 'failure',
                   'details': 'Queue is not exists.'}

        return REST_COMMAND_RESULT, msg

    @rest_command
    def set_queue(self, rest, vlan_id):
        if self.ovs_bridge is None:
            msg = {'result': 'failure',
                   'details': 'ovs_bridge is not exists'}
            return REST_COMMAND_RESULT, msg

        self.queue_list.clear()
        queue_type = rest.get(REST_QUEUE_TYPE, 'linux-htb')
        parent_max_rate = rest.get(REST_QUEUE_MAX_RATE, None)
        queues = rest.get(REST_QUEUES, [])
        queue_id = 0
        queue_config = []
        for queue in queues:
            max_rate = queue.get(REST_QUEUE_MAX_RATE, None)
            min_rate = queue.get(REST_QUEUE_MIN_RATE, None)
            if max_rate is None and min_rate is None:
                raise ValueError('Required to specify max_rate or
min_rate')
            config = {}
            if max_rate is not None:
                config['max-rate'] = max_rate
            if min_rate is not None:
                config['min-rate'] = min_rate
            if len(config):
                queue_config.append(config)
            self.queue_list[queue_id] = {'config': config}
            queue_id += 1

        port_name = rest.get(REST_PORT_NAME, None)
        vif_ports = self.ovs_bridge.get_port_name_list()

        if port_name is not None:
            if port_name not in vif_ports:
                raise ValueError('%s port is not exists' %
port_name)
            vif_ports = [port_name]
```

```
        for port_name in vif_ports:
            try:
                self.ovs_bridge.set_qos(port_name, type=queue_type,
                                        max_rate=parent_max_rate,
                                        queues=queue_config)
            except Exception as msg:
                raise ValueError(msg)

        msg = {'result': 'success',
               'details': self.queue_list}

        return REST_COMMAND_RESULT, msg

    def _delete_queue(self):
        if self.ovs_bridge is None:
            return False

        vif_ports = self.ovs_bridge.get_external_ports()
        for port in vif_ports:
            self.ovs_bridge.del_qos(port.port_name)
        return True

    @rest_command
    def delete_queue(self, rest, vlan_id):
        self.queue_list.clear()
        if self._delete_queue():
            msg = 'success'
        else:
            msg = 'failure'

        return REST_COMMAND_RESULT, msg

    @rest_command
    def set_qos(self, rest, vlan_id, waiters):
        msgs = []
        cookie_list = self._get_cookie(vlan_id)
        for cookie, vid in cookie_list:
            msg = self._set_qos(cookie, rest, waiters, vid)
            msgs.append(msg)
        return REST_COMMAND_RESULT, msgs

    def _set_qos(self, cookie, rest, waiters, vlan_id):
        match_value = rest[REST_MATCH]
        if vlan_id:
            match_value[REST_DL_VLAN] = vlan_id

        priority = int(rest.get(REST_PRIORITY, QOS_PRIORITY_MIN))
        if (QOS_PRIORITY_MAX < priority):
            raise ValueError('Invalid priority value. Set [%d-%d]'
                             % (QOS_PRIORITY_MIN, QOS_PRIORITY_MAX))

        match = Match.to_openflow(match_value)

        actions = []
        action = rest.get(REST_ACTION, None)
```

```
        if action is not None:
            if REST_ACTION_MARK in action:
                actions.append({'type': 'SET_FIELD',
                                'field': REST_DSCP,
                                'value':
int(action[REST_ACTION_MARK])})
            if REST_ACTION_METER in action:
                actions.append({'type': 'METER',
                                'meter_id':
action[REST_ACTION_METER]})
            if REST_ACTION_QUEUE in action:
                actions.append({'type': 'SET_QUEUE',
                                'queue_id':
action[REST_ACTION_QUEUE]})
        else:
            actions.append({'type': 'SET_QUEUE',
                            'queue_id': 0})

        actions.append({'type': 'GOTO_TABLE',
                        'table_id': QOS_TABLE_ID + 1})
        flow = self._to_of_flow(cookie=cookie, priority=priority,
                                match=match, actions=actions)

        cmd = self.dp.ofproto.OFPFC_ADD
        try:
            self.ofctl.mod_flow_entry(self.dp, flow, cmd)
        except:
            raise ValueError('Invalid rule parameter.')

        qos_id = QoS._cookie_to_qosid(cookie)
        msg = {'result': 'success',
               'details': 'QoS added. : qos_id=%d' % qos_id}

        if vlan_id != VLANID_NONE:
            msg.setdefault(REST_VLANID, vlan_id)
        return msg

    @rest_command
    def get_qos(self, rest, vlan_id, waiters):
        rules = {}
        msgs = self.ofctl.get_flow_stats(self.dp, waiters)
        if str(self.dp.id) in msgs:
            flow_stats = msgs[str(self.dp.id)]
            for flow_stat in flow_stats:
                if flow_stat['table_id'] != QOS_TABLE_ID:
                    continue
                priority = flow_stat[REST_PRIORITY]
                if priority != DEFAULT_FLOW_PRIORITY:
                    vid = flow_stat[REST_MATCH].get(REST_DL_VLAN,
VLANID_NONE)
                    if vlan_id == REST_ALL or vlan_id == vid:
                        rule = self._to_rest_rule(flow_stat)
                        rules.setdefault(vid, [])
                        rules[vid].append(rule)
```

```
        get_data = []
        for vid, rule in rules.items():
            if vid == VLANID_NONE:
                vid_data = {REST_QOS: rule}
            else:
                vid_data = {REST_VLANID: vid, REST_QOS: rule}
            get_data.append(vid_data)

        return REST_COMMAND_RESULT, get_data

    @rest_command
    def delete_qos(self, rest, vlan_id, waiters):
        try:
            if rest[REST_QOS_ID] == REST_ALL:
                qos_id = REST_ALL
            else:
                qos_id = int(rest[REST_QOS_ID])
        except:
            raise ValueError('Invalid qos id.')

        vlan_list = []
        delete_list = []

        msgs = self.ofctl.get_flow_stats(self.dp, waiters)
        if str(self.dp.id) in msgs:
            flow_stats = msgs[str(self.dp.id)]
            for flow_stat in flow_stats:
                cookie = flow_stat[REST_COOKIE]
                ruleid = QoS._cookie_to_qosid(cookie)
                priority = flow_stat[REST_PRIORITY]
                dl_vlan = flow_stat[REST_MATCH].get(REST_DL_VLAN,
VLANID_NONE)

                if priority != DEFAULT_FLOW_PRIORITY:
                    if ((qos_id == REST_ALL or qos_id == ruleid)
and
                            (vlan_id == dl_vlan or vlan_id ==
REST_ALL)):
                        match =
Match.to_mod_openflow(flow_stat[REST_MATCH])
                        delete_list.append([cookie, priority,
match])
                    else:
                        if dl_vlan not in vlan_list:
                            vlan_list.append(dl_vlan)

        self._update_vlan_list(vlan_list)

        if len(delete_list) == 0:
            msg_details = 'QoS rule is not exist.'
            if qos_id != REST_ALL:
                msg_details += ' : QoS ID=%d' % qos_id
            msg = {'result': 'failure',
                   'details': msg_details}
        else:
```

```
            cmd = self.dp.ofproto.OFPFC_DELETE_STRICT
            actions = []
            delete_ids = {}
            for cookie, priority, match in delete_list:
                flow = self._to_of_flow(cookie=cookie,
priority=priority,
                                        match=match,
actions=actions)
                self.ofctl.mod_flow_entry(self.dp, flow, cmd)

                vid = match.get(REST_DL_VLAN, VLANID_NONE)
                rule_id = QoS._cookie_to_qosid(cookie)
                delete_ids.setdefault(vid, '')
                delete_ids[vid] += (('%d' if delete_ids[vid] == ''
                                     else ',%d') % rule_id)

            msg = []
            for vid, rule_ids in delete_ids.items():
                del_msg = {'result': 'success',
                           'details': ' deleted. : QoS ID=%s' %
rule_ids}
                if vid != VLANID_NONE:
                    del_msg.setdefault(REST_VLANID, vid)
                msg.append(del_msg)

        return REST_COMMAND_RESULT, msg

    @rest_command
    def set_meter(self, rest, vlan_id, waiters):
        if self.version == ofproto_v1_0.OFP_VERSION:
            raise ValueError('set_meter operation is not supported')

        msgs = []
        msg = self._set_meter(rest, waiters)
        msgs.append(msg)
        return REST_COMMAND_RESULT, msgs

    def _set_meter(self, rest, waiters):
        cmd = self.dp.ofproto.OFPMC_ADD
        try:
            self.ofctl.mod_meter_entry(self.dp, rest, cmd)
        except:
            raise ValueError('Invalid meter parameter.')

        msg = {'result': 'success',
               'details': 'Meter added. : Meter ID=%s' %
               rest[REST_METER_ID]}
        return msg

    @rest_command
    def get_meter(self, rest, vlan_id, waiters):
        if (self.version == ofproto_v1_0.OFP_VERSION or
                self.version == ofproto_v1_2.OFP_VERSION):
            raise ValueError('get_meter operation is not supported')
```

```
        msgs = self.ofctl.get_meter_stats(self.dp, waiters)
        return REST_COMMAND_RESULT, msgs

    @rest_command
    def delete_meter(self, rest, vlan_id, waiters):
        if (self.version == ofproto_v1_0.OFP_VERSION or
                self.version == ofproto_v1_2.OFP_VERSION):
            raise ValueError('delete_meter operation is not
supported')

        cmd = self.dp.ofproto.OFPMC_DELETE
        try:
            self.ofctl.mod_meter_entry(self.dp, rest, cmd)
        except:
            raise ValueError('Invalid meter parameter.')

        msg = {'result': 'success',
               'details': 'Meter deleted. : Meter ID=%s' %
               rest[REST_METER_ID]}
        return REST_COMMAND_RESULT, msg

    def _to_of_flow(self, cookie, priority, match, actions):
        flow = {'cookie': cookie,
                'priority': priority,
                'flags': 0,
                'idle_timeout': 0,
                'hard_timeout': 0,
                'match': match,
                'actions': actions}
        return flow

    def _to_rest_rule(self, flow):
        ruleid = QoS._cookie_to_qosid(flow[REST_COOKIE])
        rule = {REST_QOS_ID: ruleid}
        rule.update({REST_PRIORITY: flow[REST_PRIORITY]})
        rule.update(Match.to_rest(flow))
        rule.update(Action.to_rest(flow))
        return rule


class Match(object):

    _CONVERT = {REST_DL_TYPE:
                {REST_DL_TYPE_ARP: ether.ETH_TYPE_ARP,
                 REST_DL_TYPE_IPV4: ether.ETH_TYPE_IP,
                 REST_DL_TYPE_IPV6: ether.ETH_TYPE_IPV6},
                REST_NW_PROTO:
                {REST_NW_PROTO_TCP: inet.IPPROTO_TCP,
                 REST_NW_PROTO_UDP: inet.IPPROTO_UDP,
                 REST_NW_PROTO_ICMP: inet.IPPROTO_ICMP,
                 REST_NW_PROTO_ICMPV6: inet.IPPROTO_ICMPV6}}

    @staticmethod
    def to_openflow(rest):
```

```
        def __inv_combi(msg):
            raise ValueError('Invalid combination: [%s]' % msg)

        def __inv_2and1(*args):
            __inv_combi('%s=%s and %s' % (args[0], args[1],
args[2]))

        def __inv_2and2(*args):
            __inv_combi('%s=%s and %s=%s' % (
                args[0], args[1], args[2], args[3]))

        def __inv_1and1(*args):
            __inv_combi('%s and %s' % (args[0], args[1]))

        def __inv_1and2(*args):
            __inv_combi('%s and %s=%s' % (args[0], args[1],
args[2]))

        match = {}

        # error check
        dl_type = rest.get(REST_DL_TYPE)
        nw_proto = rest.get(REST_NW_PROTO)
        if dl_type is not None:
            if dl_type == REST_DL_TYPE_ARP:
                if REST_SRC_IPV6 in rest:
                    __inv_2and1(
                        REST_DL_TYPE, REST_DL_TYPE_ARP,
REST_SRC_IPV6)
                if REST_DST_IPV6 in rest:
                    __inv_2and1(
                        REST_DL_TYPE, REST_DL_TYPE_ARP,
REST_DST_IPV6)
                if REST_DSCP in rest:
                    __inv_2and1(
                        REST_DL_TYPE, REST_DL_TYPE_ARP, REST_DSCP)
                if nw_proto:
                    __inv_2and1(
                        REST_DL_TYPE, REST_DL_TYPE_ARP,
REST_NW_PROTO)
            elif dl_type == REST_DL_TYPE_IPV4:
                if REST_SRC_IPV6 in rest:
                    __inv_2and1(
                        REST_DL_TYPE, REST_DL_TYPE_IPV4,
REST_SRC_IPV6)
                if REST_DST_IPV6 in rest:
                    __inv_2and1(
                        REST_DL_TYPE, REST_DL_TYPE_IPV4,
REST_DST_IPV6)
                if nw_proto == REST_NW_PROTO_ICMPV6:
                    __inv_2and2(
                        REST_DL_TYPE, REST_DL_TYPE_IPV4,
                        REST_NW_PROTO, REST_NW_PROTO_ICMPV6)
            elif dl_type == REST_DL_TYPE_IPV6:
                if REST_SRC_IP in rest:
```

```
                    __inv_2and1(
                        REST_DL_TYPE, REST_DL_TYPE_IPV6,
REST_SRC_IP)
                if REST_DST_IP in rest:
                    __inv_2and1(
                        REST_DL_TYPE, REST_DL_TYPE_IPV6,
REST_DST_IP)
                if nw_proto == REST_NW_PROTO_ICMP:
                    __inv_2and2(
                        REST_DL_TYPE, REST_DL_TYPE_IPV6,
                        REST_NW_PROTO, REST_NW_PROTO_ICMP)
            else:
                raise ValueError('Unknown dl_type : %s' % dl_type)
        else:
            if REST_SRC_IP in rest:
                if REST_SRC_IPV6 in rest:
                    __inv_1and1(REST_SRC_IP, REST_SRC_IPV6)
                if REST_DST_IPV6 in rest:
                    __inv_1and1(REST_SRC_IP, REST_DST_IPV6)
                if nw_proto == REST_NW_PROTO_ICMPV6:
                    __inv_1and2(
                        REST_SRC_IP, REST_NW_PROTO,
REST_NW_PROTO_ICMPV6)
                rest[REST_DL_TYPE] = REST_DL_TYPE_IPV4
            elif REST_DST_IP in rest:
                if REST_SRC_IPV6 in rest:
                    __inv_1and1(REST_DST_IP, REST_SRC_IPV6)
                if REST_DST_IPV6 in rest:
                    __inv_1and1(REST_DST_IP, REST_DST_IPV6)
                if nw_proto == REST_NW_PROTO_ICMPV6:
                    __inv_1and2(
                        REST_DST_IP, REST_NW_PROTO,
REST_NW_PROTO_ICMPV6)
                rest[REST_DL_TYPE] = REST_DL_TYPE_IPV4
            elif REST_SRC_IPV6 in rest:
                if nw_proto == REST_NW_PROTO_ICMP:
                    __inv_1and2(
                        REST_SRC_IPV6, REST_NW_PROTO,
REST_NW_PROTO_ICMP)
                rest[REST_DL_TYPE] = REST_DL_TYPE_IPV6
            elif REST_DST_IPV6 in rest:
                if nw_proto == REST_NW_PROTO_ICMP:
                    __inv_1and2(
                        REST_DST_IPV6, REST_NW_PROTO,
REST_NW_PROTO_ICMP)
                rest[REST_DL_TYPE] = REST_DL_TYPE_IPV6
            elif REST_DSCP in rest:
                # Apply dl_type ipv4, if doesn't specify dl_type
                rest[REST_DL_TYPE] = REST_DL_TYPE_IPV4
            else:
                if nw_proto == REST_NW_PROTO_ICMP:
                    rest[REST_DL_TYPE] = REST_DL_TYPE_IPV4
                elif nw_proto == REST_NW_PROTO_ICMPV6:
                    rest[REST_DL_TYPE] = REST_DL_TYPE_IPV6
                elif nw_proto == REST_NW_PROTO_TCP or \
```

```
                        nw_proto == REST_NW_PROTO_UDP:
                    raise ValueError('no dl_type was specified')
                else:
                    raise ValueError('Unknown nw_proto: %s' %
nw_proto)

        for key, value in rest.items():
            if key in Match._CONVERT:
                if value in Match._CONVERT[key]:
                    match.setdefault(key,
Match._CONVERT[key][value])
                else:
                    raise ValueError('Invalid rule parameter. :
key=%s' % key)
            else:
                match.setdefault(key, value)

        return match

    @staticmethod
    def to_rest(openflow):
        of_match = openflow[REST_MATCH]

        mac_dontcare = mac.haddr_to_str(mac.DONTCARE)
        ip_dontcare = '0.0.0.0'
        ipv6_dontcare = '::'

        match = {}
        for key, value in of_match.items():
            if key == REST_SRC_MAC or key == REST_DST_MAC:
                if value == mac_dontcare:
                    continue
            elif key == REST_SRC_IP or key == REST_DST_IP:
                if value == ip_dontcare:
                    continue
            elif key == REST_SRC_IPV6 or key == REST_DST_IPV6:
                if value == ipv6_dontcare:
                    continue
            elif value == 0:
                continue

            if key in Match._CONVERT:
                conv = Match._CONVERT[key]
                conv = dict((value, key) for key, value in
conv.items())
                match.setdefault(key, conv[value])
            else:
                match.setdefault(key, value)

        return match

    @staticmethod
    def to_mod_openflow(of_match):
        mac_dontcare = mac.haddr_to_str(mac.DONTCARE)
        ip_dontcare = '0.0.0.0'
```

```
        ipv6_dontcare = '::'

        match = {}
        for key, value in of_match.items():
            if key == REST_SRC_MAC or key == REST_DST_MAC:
                if value == mac_dontcare:
                    continue
            elif key == REST_SRC_IP or key == REST_DST_IP:
                if value == ip_dontcare:
                    continue
            elif key == REST_SRC_IPV6 or key == REST_DST_IPV6:
                if value == ipv6_dontcare:
                    continue
            elif value == 0:
                continue

            match.setdefault(key, value)

        return match


class Action(object):

    @staticmethod
    def to_rest(openflow):
        if REST_ACTION in openflow:
            actions = []
            for action in openflow[REST_ACTION]:
                field_value = re.search('SET_FIELD: {ip_dscp:(\d+)',
action)
                if field_value:
                    actions.append({REST_ACTION_MARK:
field_value.group(1)})
                meter_value = re.search('METER:(\d+)', action)
                if meter_value:
                    actions.append({REST_ACTION_METER:
meter_value.group(1)})
                queue_value = re.search('SET_QUEUE:(\d+)', action)
                if queue_value:
                    actions.append({REST_ACTION_QUEUE:
queue_value.group(1)})
                action = {REST_ACTION: actions}
        else:
            action = {REST_ACTION: 'Unknown action type.'}

        return action
```

5.3 SwitchPort Monitoring and Queue Calculator Constructs

(a) Switch Port Monitoring

```
#!/usr/bin/bash

while true
do
cat stats1.log > stats1.old
cat stats2.log > stats2.old
curl -X GET http://localhost:8080/stats/port/000000000001 >
raw1.log
curl -X GET http://localhost:8080/stats/port/000000000002 >
raw2.log
cat raw1.log | awk '{gsub ("tx_dropped", "\ntx_dropped") } 1' |
column -t | awk '{print $ 11 $12 $7 $8 $17 $ 18 $19 $20 $27 $28 $23
$24}' | column -t -s ',' | column -t -s ':' | sort -k2 -n >
stats1.log
cat raw2.log | awk '{gsub ("tx_dropped", "\ntx_dropped") } 1' |
column -t | awk '{print $ 11 $12 $7 $8 $17 $ 18 $19 $20 $27 $28 $23
$24}' | column -t -s ',' | column -t -s ':' | sort -k2 -n >
stats2.log
rm raw1.log raw2.log
echo " "
echo "SWITCH S1"
echo "========="
cat stats1.log
echo " "
echo "SWITCH S2"
echo "========="
cat stats2.log
echo " "
paste stats1.log stats1.old | awk '{for (i=0;i<=NF/2;i++) printf
"%s ", ($i==$i+0)?$i-$(i+NF/2):$i; print ""}' | awk '{print $1 " "
$2 " " $27 " " $28 " " $29 " " $30 " " $31 " "  $32 " " $33 " "$34
" " $35 " " $36}' | column -t > diff.log
echo "================================= "
echo "PORT STATS (DIFFERENCE) SWITCH S1"
echo "================================="
cat diff.log
echo " "
cat diff.log | awk '{print $4}' | tr '\n' ' ' > diff-linear.log

awk '{if ($2 > "100" && $3 > "100") system("bash -c '\''" "bash
config1.sh" "'\''")}' diff-linear.log
awk '{if ($2 < "10" && $3 < "10" && $4 < "10" && $5 < "10" && $6 <
"10" && $7 < "10" && $8 < "10" && $9 < "10" && $11 < "10" && $12 <
"10" && $13 < "10") system("bash -c '\''" "bash remove-config.sh"
"'\''")}' diff-linear.log

echo " "
sleep 10

done
```

(b) Queue Installation

```
#!/usr/bin/bash

#============================
#RYU CONTROLLER INSTALLATION
#============================
#git clone git://github.com/osrg/ryu.git
#time sudo apt-get install python-eventlet python-routes python-
webob python-paramiko
#sudo killall controller
#cd ryu
#sudo ./setup.py install
#sudo install ryu
#./bin/ryu-manager ryu/app/simple_switch.py

#===========
#SETTING QOS
#===========
#SET SWITCH:
ovs-vsctl set Bridge s1 protocols=OpenFlow13,OpenFlow14
ovs-vsctl set-manager ptcp:6632

#SET CONTROLLER AND ENABLE QOS:
sed '/OFPFlowMod(/,/)/s/)/, table_id=1)/'
ryu/ryu/app/simple_switch_13.py >
ryu/ryu/app/qos_simple_switch_13.py OR
PYTHONPATH=. ./bin/ryu-manager ryu/app/rest_qos
ryu/app/qos_simple_switch_13 ryu/app/rest_conf_switch
ryu/app/ofctl_rest

cd ryu/; python ./setup.py install
ryu-manager ryu.app.rest_qos ryu.app.qos_simple_switch_13
ryu.app.rest_conf_switch ryu.app.ofctl_rest
curl -X PUT -d '"tcp:127.0.0.1:6632"'
http://localhost:8080/v1.0/conf/switches/0000000000000001/ovsdb_add
r
curl -X PUT -d '"tcp:127.0.0.1:6632"'
http://localhost:8080/v1.0/conf/switches/0000000000000002/ovsdb_add
r

#==============
#DISPLAY QUEUES
#==============

curl -X GET http://localhost:8080/qos/rules/0000000000000001
curl -X GET http://localhost:8080/qos/rules/0000000000000002

#=========
#SET QUEUE
#=========
#Q1:
curl -X POST -d '{"port_name": "s1-eth1", "type": "linux-htb",
"max_rate": "2000000", "queues": [{"max_rate": "2000000"},
```

```
{"max_rate": "250000"}, {"max_rate": "62500"}, {"max_rate":
"510000"}, {"max_rate": "600000"}, {"max_rate": "100000"},
{"max_rate": "175000"}]}'
http://localhost:8080/qos/queue/0000000000000001
#Q2:
curl -X POST -d '{"port_name": "s1-eth1", "type": "linux-htb",
"max_rate": "2000000", "queues": [{"max_rate": "2000000"},
{"max_rate": "250000"}, {"max_rate": "62500"}, {"max_rate":
"680000"}, {"max_rate": "900000"}, {"max_rate": "100000"}]}'
http://localhost:8080/qos/queue/0000000000000001
#Q3:
curl -X POST -d '{"port_name": "s1-eth1", "type": "linux-htb",
"max_rate": "2000000", "queues": [{"max_rate": "2000000"},
{"max_rate": "500000"}, {"max_rate": "187500"}, {"max_rate":
"680000"}, {"max_rate": "600000"}]}'
http://localhost:8080/qos/queue/0000000000000001

#Q1: Service Proiver:
curl -X POST -d '{"port_name": "s2-eth1", "type": "linux-htb",
"max_rate": "20000000", "queues": [{"max_rate": "20000000"},
{"max_rate": "250000"}, {"max_rate": "500000"}, {"max_rate":
"1000000"}, {"max_rate": "2000000"}, {"max_rate": "3000000"}]}'
http://localhost:8080/qos/queue/0000000000000002

#===========
#APPLY QUEUE
#===========
#OUTBOUND QUEUES
#===============

curl -X POST -d '{"match": {"nw_src": "10.0.0.3"},
"actions":{"queue": "1"}}'
http://localhost:8080/qos/rules/0000000000000001
curl -X POST -d '{"match": {"nw_src": "10.0.0.4"},
"actions":{"queue": "2"}}'
http://localhost:8080/qos/rules/0000000000000001
curl -X POST -d '{"match": {"nw_src": "10.0.0.10"},
"actions":{"queue": "3"}}'
http://localhost:8080/qos/rules/0000000000000001
curl -X POST -d '{"match": {"nw_src": "10.0.0.22"},
"actions":{"queue": "3"}}'
http://localhost:8080/qos/rules/0000000000000001
curl -X POST -d '{"match": {"nw_src": "10.0.0.23"},
"actions":{"queue": "3"}}'
http://localhost:8080/qos/rules/0000000000000001
curl -X POST -d '{"match": {"nw_src": "10.0.0.6"},
"actions":{"queue": "4"}}'
http://localhost:8080/qos/rules/0000000000000001
curl -X POST -d '{"match": {"nw_src": "10.0.0.7"},
"actions":{"queue": "4"}}'
http://localhost:8080/qos/rules/0000000000000001
curl -X POST -d '{"match": {"nw_src": "10.0.0.24"},
"actions":{"queue": "5"}}'
http://localhost:8080/qos/rules/0000000000000001
```

```
curl    -X    POST    -d    '{"match":    {"nw_src":    "10.0.0.25"},
"actions":{"queue":                                          "6"}}'
http://localhost:8080/qos/rules/0000000000000001

#=============
#IBOUND QUEUES
#=============
curl    -X    POST    -d    '{"match":    {"nw_dst":    "10.0.0.3"},
"actions":{"queue":                                          "2"}}'
http://localhost:8080/qos/rules/0000000000000002
curl    -X    POST    -d    '{"match":    {"nw_dst":    "10.0.0.4"},
"actions":{"queue":                                          "2"}}'
http://localhost:8080/qos/rules/0000000000000002
#=========================
#CLEAR ALL QUEUES
#=========================

curl    -X    POST    -d    '{"match":    {"nw_src":    "10.0.0.3"},
"actions":{"queue":                                          "0"}}'
http://localhost:8080/qos/rules/0000000000000001
curl    -X    POST    -d    '{"match":    {"nw_src":    "10.0.0.4"},
"actions":{"queue":                                          "0"}}'
http://localhost:8080/qos/rules/0000000000000001
curl    -X    POST    -d    '{"match":    {"nw_src":    "10.0.0.10"},
"actions":{"queue":                                          "0"}}'
http://localhost:8080/qos/rules/0000000000000001
curl    -X    POST    -d    '{"match":    {"nw_src":    "10.0.0.22"},
"actions":{"queue":                                          "0"}}'
http://localhost:8080/qos/rules/0000000000000001
curl    -X    POST    -d    '{"match":    {"nw_src":    "10.0.0.23"},
"actions":{"queue":                                          "0"}}'
http://localhost:8080/qos/rules/0000000000000001
curl    -X    POST    -d    '{"match":    {"nw_src":    "10.0.0.6"},
"actions":{"queue":                                          "0"}}'
http://localhost:8080/qos/rules/0000000000000001
curl    -X    POST    -d    '{"match":    {"nw_src":    "10.0.0.7"},
"actions":{"queue":                                          "0"}}'
http://localhost:8080/qos/rules/0000000000000001
curl    -X    POST    -d    '{"match":    {"nw_src":    "10.0.0.24"},
"actions":{"queue":                                          "0"}}'
http://localhost:8080/qos/rules/0000000000000001
curl    -X    POST    -d    '{"match":    {"nw_src":    "10.0.0.25"},
"actions":{"queue":                                          "0"}}'
http://localhost:8080/qos/rules/0000000000000001
curl    -X    POST    -d    '{"match":    {"nw_dst":    "10.0.0.3"},
"actions":{"queue":                                          "0"}}'
http://localhost:8080/qos/rules/0000000000000002
curl    -X    POST    -d    '{"match":    {"nw_dst":    "10.0.0.4"},
"actions":{"queue":                                          "0"}}'
http://localhost:8080/qos/rules/0000000000000002

#OR

#ovs-vsctl --all destroy qos
#ovs-vsctl --all destroy queue
```

5.4 Traffic Monitor and Route Installation

(a) Real-time traffic monitor - Port Monitoring Module (Ryu)

```
from operator import attrgetter
from ryu.app import simple_switch_13
from ryu.controller import ofp_event
from ryu.controller.handler import MAIN_DISPATCHER, DEAD_DISPATCHER
from ryu.controller.handler import set_ev_cls
from ryu.lib import hub


class SimpleMonitor(simple_switch_13.SimpleSwitch13):

    def __init__(self, *args, **kwargs):
        super(SimpleMonitor, self).__init__(*args, **kwargs)
        self.datapaths = {}
        self.monitor_thread = hub.spawn(self._monitor)

    @set_ev_cls(ofp_event.EventOFPStateChange,
                [MAIN_DISPATCHER, DEAD_DISPATCHER])
    def _state_change_handler(self, ev):
        datapath = ev.datapath
        if ev.state == MAIN_DISPATCHER:
            if not datapath.id in self.datapaths:
                self.logger.debug('register datapath: %016x',
datapath.id)
                self.datapaths[datapath.id] = datapath
        elif ev.state == DEAD_DISPATCHER:
            if datapath.id in self.datapaths:
                self.logger.debug('unregister datapath: %016x',
datapath.id)
                del self.datapaths[datapath.id]

    def _monitor(self):
        while True:
            for dp in self.datapaths.values():
                self._request_stats(dp)
            hub.sleep(1)

    def _request_stats(self, datapath):
        self.logger.debug('send stats request: %016x', datapath.id)
        ofproto = datapath.ofproto
        parser = datapath.ofproto_parser

        req = parser.OFPFlowStatsRequest(datapath)
        datapath.send_msg(req)

        req = parser.OFPPortStatsRequest(datapath, 0,
ofproto.OFPP_ANY)
        datapath.send_msg(req)

    @set_ev_cls(ofp_event.EventOFPFlowStatsReply, MAIN_DISPATCHER)
    def _flow_stats_reply_handler(self, ev):
```

```
        body = ev.msg.body

        self.logger.info('datapath         '
                         'in-port  eth-dst           '
                         'out-port packets  bytes')
        self.logger.info('---------------- '
                         '-------- ----------------- '
                         '-------- -------- --------')
        for stat in sorted([flow for flow in body if flow.priority
== 1],
                           key=lambda flow: (flow.match['in_port'],

flow.match['eth_dst'])):
            self.logger.info('%016x %8x %17s %8x %8d %8d',
                             ev.msg.datapath.id,
                             stat.match['in_port'],
stat.match['eth_dst'],
                             stat.instructions[0].actions[0].port,
                             stat.packet_count, stat.byte_count)

    @set_ev_cls(ofp_event.EventOFPPortStatsReply, MAIN_DISPATCHER)
    def _port_stats_reply_handler(self, ev):
        body = ev.msg.body

        self.logger.info('datapath         port     '
                         'rx-pkts  rx-bytes rx-error '
                         'tx-pkts  tx-bytes tx-error')
        self.logger.info('---------------- -------- '
                         '-------- -------- -------- '
                         '-------- -------- --------')
        for stat in sorted(body, key=attrgetter('port_no')):
            self.logger.info('%016x %8x %8d %8d %8d %8d %8d %8d',
                             ev.msg.datapath.id, stat.port_no,
                             stat.rx_packets, stat.rx_bytes,
stat.rx_errors,
                             stat.tx_packets, stat.tx_bytes,
stat.tx_errors)
```

(b) Route Installation

```
portstats.sh
#!/usr/bin/bash

ryu-manager ./simple_monitor.py | tee stats.log

while true
do

cat stats.log >> stats.old
cat stats.log | awk '{print $1" "$2" "$3}' > stats_updated.log
```

```
paste stats1.log stats1.old | awk '{for (i=0;i<=NF/2;i++) printf
"%s ", ($i==$i+0)?$i-$(i+NF/2):$i; print ""}' | awk '{print $1 " "
$2" "$3}' | column -t > diff.log
echo "==================================== "
echo "PORT STATS (DIFFERENCE) SWITCH S1 & S2"
echo "===================================="
cat diff.log
echo " "
cat diff.log | awk '{print $0}' | tr '\n' ' ' > diff-linear.log

#profile 1: port, 1-2 SW1
#profile 1: port, 1-2 SW2
#profile 2: port, 3-4 SW1
#profile 2: port, 3-4 SW2
#profile 3: port, 5-6 SW1
#profile 3: port, 5-6 SW2
#profile 4: port, 7-8 SW1
#profile 4: port, 7-8 SW2
#profile 5: port, 9-10 SW1
#profile 5: port, 9-10 SW2
#profile 6: port, 11-12 SW1
#profile 6: port, 11-12 SW2
#profile 7: port, 13-14 SW1
#profile 7: port, 13-14 SW2

for i in {100,200,300,400,500,600,700};
do
awk '{if ($3 > "1" && $2 > "1" && $1 = "0000000000000001" || $1 =
"0000000000000002") system("bash -c '\''" "bash config$i.sh"
"'\''")}' diff-linear.log
echo " "
sleep 60
done

echo " "
sleep 10

done
```

Example: **config.sh**

```
#!/usr/bin/bash

echo "Enter the number of user load per profile, followed by
[ENTER]:"
read user_load

echo_time() {
    date +"%R:%S $*"
                }
echo_time "Simulation start time"

lt_core_dist_dn = 10000000000
lt_dist_access_dn = 10000000000
lt_core_dist_up = 10000000000
lt_dist_access_up = 10000000000
```

```
for p in {1..7}
 do
   for app_direction in {1..8}
   do
      for dn in {1..2}
      #compute core-dist link
       #total links: 4
       do while user_load > 1
                for l in {1..4}
                do
                     B=$(cat B_profile_$p_$app_$direction.dat)
                     lt_$l = lt_core_dist_dn
                     u_max_core_dist_$dn = "$lt_l /$B" | bc

                if u_max_core_dist_$dn >= user_load && lt_l > 0

                for i in {1..2}
                          do
                          for j in {1..7}
                               do
                                    for x in {1..8}
                                    do
                                    curl -X POST -d '{"match":
{"nw_src": "10.'$j'.0.0/16"}, "actions":{"table1"}}'
http://localhost:8080/qos/rules/000000000000000'$i'
                                    curl -X POST -d '{"match":
{"table_id": "1","nw_src": "10.'$j'.0.0/16", "nw_dst":
"10.0.0.'$x'"}, "actions":{set "vlan_id":"1'$j$dn'",
"output":"$l"}}'
http://localhost:8080/qos/rules/000000000000000'$i'
                                    echo_time
                                    #barrier message
                                    curl -X POST -d
'{ "OFPBarrierRequest": {} }
'http://localhost:8080/qos/rules/000000000000000'$i'
                                    echo_time
                                    echo "Core - Routes
Installed"
                               done
                          done
                lt_l = "$lt_core_dist_dn - $user_load * $B" | bc

                if u_max_core_dist_dn >= user_load && lt_l > 0
                max_users = user_load - user_load/lt_l

                for i in {1..2}
                          do
                          for j in {1..7}
                               do
                                    for x in {1..8}
                                    do
                                    curl -X POST -d '{"match":
{"nw_src": "10.'$j'.0.0/16"}, "actions":{"table2"}}'
http://localhost:8080/qos/rules/000000000000000'$i'
```

```
                                        curl -X POST -d '{"match":
{"table_id": "2","nw_src": "10.'$j'.0.0/16", "nw_dst":
"10.0.0.'$x'"}, "actions":{set "vlan_id":"2'$j$dn'",
"output":"$l"}}'
http://localhost:8080/qos/rules/000000000000000'$i'
                                        echo_time
                                        #barrier message
                                        curl -X POST -d
'{ "OFPBarrierRequest": {} }
'http://localhost:8080/qos/rules/000000000000000'$i'
                                        echo_time
                                        echo "Core - Routes
Installed"
                                  done
                            done
                  done


                  for l in {1..2}
                  do
                        B=$(cat B_profile_$p_$app_$direction.dat)
                        lt_$l = lt_core_dist_dn
                        u_max_core_dist_$dn = "$lt_l /$B" | bc

                  if u_max_core_dist_$dn >= user_load && lt_l > 0

                  for i in {1..2}
                            do
                            for j in {1..7}
                                  do
                                        for x in {1..8}
                                        do
                                        curl -X POST -d '{"match":
{"nw_dst": "10.0.0.'$x'/16", "vlan_id":"10'$j'"},
"actions":{"output":"$l"}}'
http://localhost:8080/qos/rules/000000000000000'$k'
                                        echo_time
                                        #barrier message
                                        curl -X POST -d
'{ "OFPBarrierRequest": {} }
'http://localhost:8080/qos/rules/000000000000000'$i'
                                        echo_time
                                        echo "Core - Routes
Installed"
                                  done
                            done
                  lt_l = "$lt_core_dist_dn - $user_load * $B" | bc

                  if u_max_core_dist_dn >= user_load && lt_l > 0
                  max_users = user_load - user_load/lt_l

                  for i in {1..2}
                            do
                            for j in {1..7}
                                  do
```

```
                                        for x in {1..8}
                                        do
                                        curl -X POST -d '{"match":
{"nw_dst": "10.0.0.'$x'/16", "vlan_id":"10'$j'"},
"actions":{"output":"$l"}}'
http://localhost:8080/qos/rules/000000000000000'$k'
                                        echo_time
                                        #barrier message
                                        curl -X POST -d
'{ "OFPBarrierRequest": {} }
'http://localhost:8080/qos/rules/000000000000000'$i'
                                        echo_time
                                        echo "Core - Routes
Installed"
                                done
                            done
                    done

for m in {11..18}
for z in {1..8}
do
curl -X POST -d '{"match": {"dl_src": "aa:bb:cc:11:11:$m", "dl_dst":
"aa:bb:cc:11:11:1'$z'"}, "actions":{"output":"1"}}'
http://localhost:8080/qos/rules/000000000000000'$z'
curl -X POST -d '{"match":"dl_src": "aa:bb:cc:11:11:$m"}}'
http://localhost:8080/stats/aggregateflow/$z
echo_time
#barrier message
curl -X POST -d '{ "OFPBarrierRequest": {} }
'http://localhost:8080/qos/rules/000000000000000'$z'
echo_time
echo "East West Traffic (Access, Distribution) - Routes Installed"
done
done

echo " "
echo "Traffic Statistics"
for u in {1..18}
do
curl -X GET http://localhost:8080/stats/table/$u
curl -X GET http://localhost:8080/stats/flow/$u
curl -X POST -d '{"match":{"vlan_id":"10'$j'"}}'
http://localhost:8080/stats/aggregateflow/$u

done

done
done
```

(c) <u>Barrier Request Support Added to Ryu Switching Application (simple_switch_13)</u>

```
Barrier Request Message
def send_barrier_request(self, datapath):
    ofp_parser = datapath.ofproto_parser
```

```
    req = ofp_parser.OFPBarrierRequest(datapath)
    datapath.send_msg(req)


Barrier Reply Message
@set_ev_cls(ofp_event.EventOFPBarrierReply, MAIN_DISPATCHER)
def barrier_reply_handler(self, ev):
    self.logger.debug('OFPBarrierReply received')
```

(d) Recording per profile, per application traffic statistics

```
#!/bin/bash
for dom in {01..30};
do
for p in {1..6}
do
cat report$dom.csv | awk -F',' '$22==1
{print$1","$2","$11","$12","$13","$14","$20}'>
profile$p_day$dom.csv
cat report$dom.csv | awk -F',' '$23==1
{print$1","$2","$11","$12","$13","$14","$20}'>
profile$p_day$dom.csv
done
done

for p in {1..6};
do
for dom in {01..30};
do
cat profile$p'_day'$dom.csv | wc -l >> num_devcs_profile$p.csv;
cat profile$p'_day'$dom.csv | awk -F',' '{print $7}' | sed /^$/d
|sort | uniq | wc -l >> num_users_profile$p.csv;
cat profile$p'_day'$dom.csv | awk -F',' '{ sum += $2; n++ } END
{ if (n > 0) print sum / n; }'>>avg_flows_profile$p.csv;
cat profile$p'_day'$dom.csv | awk -F',' '{ sum += $5; n++ } END
{ if (n > 0) print sum / n; }'>>avg_Tx_Bytes_profile$p.csv;
cat profile$p'_day'$dom.csv | awk -F',' '{ sum += $6; n++ } END
{ if (n > 0) print sum / n; }'>>avg_Rx_Bytes_profile$p.csv;
cat profile$p'_day'$dom.csv | awk -F',' '{ sum += $3; n++ } END
{ if (n > 0) print sum / n; }'>>avg_Tx_Flow_duration_profile$p.csv;
cat profile$p'_day'$dom.csv | awk -F',' '{ sum += $4; n++ } END
{ if (n > 0) print sum / n; }'>>avg_Rx_Flow_duration_profile$p.csv;
done;
done;

for i in {1..6};
do
awk '{printf("%s,", $0)}' num_devcs_profile$i.csv >>
temp_num_devices_week1.csv;
awk '{printf("%s,", $0)}' num_users_profile$i.csv>>
temp_num_users_week1.csv;
```

```
awk '{printf("%s,", $0)}' avg_flows_profile$i.csv >>
temp_avg_flows_week1.csv;
awk '{printf("%s,", $0)}' avg_Tx_Bytes_profile$i.csv >>
temp_avg_Tx_Bytes_week1.csv;
awk '{printf("%s,", $0)}' avg_Rx_Bytes_profile$i.csv >>
temp_avg_Rx_Bytes_week1.csv;
awk '{printf("%s,", $0)}' avg_Tx_Flow_duration_profile$i.csv>>
temp_avg_Tx_Flow_duration_week1.csv;
awk '{printf("%s,", $0)}' avg_Rx_Flow_duration_profile$i.csv>>
temp_avg_Rx_Flow_duration_week1.csv;
done;


cat temp_num_devices_week1.csv | awk -F',' '{print
$1","$2","$3","$4","$5","$6","$7"\n"
$8","$9","$10","$11","$12","$13","$14"\n"
$15","$16","$17","$18","$19","$20","$21"\n"
$22","$23","$24","$25","$26","$27","$28"\n"}' > num_devcs_week1.csv;
cat temp_num_users_week1.csv   | awk -F',' '{print
$1","$2","$3","$4","$5","$6","$7"\n"
$8","$9","$10","$11","$12","$13","$14"\n"
$15","$16","$17","$18","$19","$20","$21"\n"
$22","$23","$24","$25","$26","$27","$28"\n"}' > num_users_week1.csv;
cat temp_avg_flows_week1.csv   | awk -F',' '{print
$1","$2","$3","$4","$5","$6","$7"\n"
$8","$9","$10","$11","$12","$13","$14"\n"
$15","$16","$17","$18","$19","$20","$21"\n"
$22","$23","$24","$25","$26","$27","$28"\n"}' > avg_flows_week1.csv;
cat temp_avg_Tx_Bytes_week1.csv| awk -F',' '{print
$1","$2","$3","$4","$5","$6","$7"\n"
$8","$9","$10","$11","$12","$13","$14"\n"
$15","$16","$17","$18","$19","$20","$21"\n"
$22","$23","$24","$25","$26","$27","$28"\n"}' >
avg_Tx_Bytes_week1.csv;
cat temp_avg_Rx_Bytes_week1.csv| awk -F',' '{print
$1","$2","$3","$4","$5","$6","$7"\n"
$8","$9","$10","$11","$12","$13","$14"\n"
$15","$16","$17","$18","$19","$20","$21"\n"
$22","$23","$24","$25","$26","$27","$28"\n"}' >
avg_Rx_Bytes_week1.csv;
cat temp_avg_Tx_Flow_duration_week1.csv | awk -F',' '{print
$1","$2","$3","$4","$5","$6","$7"\n"
$8","$9","$10","$11","$12","$13","$14"\n"
$15","$16","$17","$18","$19","$20","$21"\n"
$22","$23","$24","$25","$26","$27","$28"\n"}' >
avg_Tx_Flow_duration_week1.csv;
cat temp_avg_Rx_Flow_duration_week1.csv | awk -F',' '{print
$1","$2","$3","$4","$5","$6","$7"\n"
$8","$9","$10","$11","$12","$13","$14"\n"
$15","$16","$17","$18","$19","$20","$21"\n"
$22","$23","$24","$25","$26","$27","$28"\n"}' >
avg_Rx_Flow_duration_week1.csv;
```

```
rm  temp_num_devices_week1.csv temp_num_users_week1.csv
temp_avg_flows_week1.csv temp_avg_Tx_Bytes_week1.csv
temp_avg_Rx_Bytes_week1.csv temp_avg_Tx_Flow_duration_week1.csv
temp_avg_Rx_Flow_duration_week1.csv

for p in {1..6}
do
for app in {1..8}
do
for direction in {1..2}
do
awk -f nfprofiler.awk segmented_report_month.csv >
B_profile_$p_$app_$direction.dat
done
done
done


rm   num_users_profile$p.csv    num_devcs_profile$p.csv
avg_flows_profile$p.csv avg_Tx_Bytes_profile$p.csv
avg_Rx_Bytes_profile$p.csv avg_Tx_Flow_duration_profile$p.csv
avg_Rx_Flow_duration_profile$p.csv;
```

5.5 OpenFlow Traffic Measurements

(a) Output Port Selection and Flow_REM flag setting in Ryu Switching Application

```
from ryu.controller import handler
from ryu.controller import dpset
from ryu.controller import ofp_event
from ryu.ofproto import ofproto_v1_3
from ryu.ofproto import ofproto_v1_3_parser
from ryu.base import app_manager
from ryu.ofproto.ofproto_parser import MsgBase, msg_pack_into,
msg_str_attr


class OF13(app_manager.RyuApp):
    OFP_VERSIONS = [ofproto_v1_3.OFP_VERSION]

    _CONTEXTS = {
        'dpset': dpset.DPSet,
        }

    def __init__(self, *args, **kwargs):
        super(OF13, self).__init__(*args, **kwargs)


    def add_flow(self, datapath, priority, match, actions):
        ofproto = datapath.ofproto
        parser = datapath.ofproto_parser

        inst =
[parser.OFPInstructionActions(ofproto.OFPIT_APPLY_ACTIONS,
```

```
                                                actions)]

        mod = parser.OFPFlowMod(datapath=datapath,
priority=priority,
                                match=match, instructions=inst,
flags=ofproto.OFPFF_SEND_FLOW_REM)
        datapath.send_msg(mod)

    @handler.set_ev_cls(dpset.EventDP, dpset.DPSET_EV_DISPATCHER)
    def handler_datapath(self, ev):
        if ev.enter:
            print "join"
            dp = ev.dp


            actions = [dp.ofproto_parser.OFPActionOutput(2)]
            match = dp.ofproto_parser.OFPMatch(in_port=1)
            self.add_flow(dp, 1, match, actions)
```

(b) Resource Monitoring Script

```
#! /bin/bash
# unset any variable which system may be using

while true
do

echo_time() {
    date +"%R:%S $*"
                }

# clear the screen
clear

unset tecreset os architecture kernelrelease internalip externalip
nameserver loadaverage

while getopts iv name
do
        case $name in
          i)iopt=1;;
          v)vopt=1;;
          *)echo "Invalid arg";;
        esac
done

if [[ ! -z $iopt ]]
then
{
wd=$(pwd)
```

```
basename "$(test -L "$0" && readlink "$0" || echo "$0")" >
/tmp/scriptname
scriptname=$(echo -e -n $wd/ && cat /tmp/scriptname)
su -c "cp $scriptname /usr/bin/monitor" root && echo
"Congratulations! Script Installed, now run monitor Command" ||
echo "Installation failed"
}
fi

if [[ ! -z $vopt ]]
then
{
echo -e "tecmint_monitor version 0.1\nDesigned by
Tecmint.com\nReleased Under Apache 2.0 License"
}
fi

if [[ $# -eq 0 ]]
then
{


# Define Variable tecreset
tecreset=$(tput sgr0)

# Check if connected to Internet or not
ping -c 1 google.com &> /dev/null && echo -e '\E[32m'"Internet:
$tecreset Connected" || echo -e '\E[32m'"Internet: $tecreset
Disconnected"

# Check OS Type
os=$(uname -o)
echo -e '\E[32m'"Operating System Type :" $tecreset $os

# Check OS Release Version and Name
cat /etc/os-release | grep 'NAME\|VERSION' | grep -v 'VERSION_ID' |
grep -v 'PRETTY_NAME' > /tmp/osrelease
echo -n -e '\E[32m'"OS Name :" $tecreset  && cat /tmp/osrelease |
grep -v "VERSION" | cut -f2 -d\"
echo -n -e '\E[32m'"OS Version :" $tecreset && cat /tmp/osrelease |
grep -v "NAME" | cut -f2 -d\"

# Check Architecture
architecture=$(uname -m)
echo -e '\E[32m'"Architecture :" $tecreset $architecture

# Check Kernel Release
kernelrelease=$(uname -r)
echo -e '\E[32m'"Kernel Release :" $tecreset $kernelrelease

# Check hostname
echo -e '\E[32m'"Hostname :" $tecreset $HOSTNAME

# Check Internal IP
internalip=$(hostname -I)
```

```
echo -e '\E[32m'"Internal IP :" $tecreset $internalip

# Check External IP
externalip=$(curl -s ipecho.net/plain;echo)
echo -e '\E[32m'"External IP : $tecreset "$externalip

# Check DNS
nameservers=$(cat /etc/resolv.conf | sed '1 d' | awk '{print $2}')
echo -e '\E[32m'"Name Servers :" $tecreset $nameservers

# Check Logged In Users
who>/tmp/who
echo -e '\E[32m'"Logged In users :" $tecreset && cat /tmp/who

# Check RAM and SWAP Usages
free -h | grep -v + > /tmp/ramcache
echo -e '\E[32m'"Ram Usages :" $tecreset
cat /tmp/ramcache | grep -v "Swap"
echo_time >> swap_usage.log
cat /tmp/ramcache | grep -v "Swap"  >> swap_usage.log
echo -e '\E[32m'"Swap Usages :" $tecreset
cat /tmp/ramcache | grep -v "Mem"
echo_time >> ram_usage.log
cat /tmp/ramcache | grep -v "Mem" >> ram_usage.log
# Check Disk Usages
df -h| grep 'Filesystem\|/dev/sda*' > /tmp/diskusage
echo -e '\E[32m'"Disk Usages :" $tecreset
cat /tmp/diskusage

# Check Load Average
loadaverage=$(top -n 1 -b | grep "load average:" | awk '{print $10
$11 $12}')
echo -e '\E[32m'"Load Average :" $tecreset $loadaverage
echo_time >> cpuload.log
echo -e '\E[32m'"Load Average :" $tecreset $loadaverage >>
cpuload.log

# Check System Uptime
tecuptime=$(uptime | awk '{print $3,$4}' | cut -f1 -d,)
echo -e '\E[32m'"System Uptime Days/(HH:MM) :" $tecreset $tecuptime

# Unset Variables
unset tecreset os architecture kernelrelease internalip externalip
nameserver loadaverage

# Remove Temporary Files
rm /tmp/osrelease /tmp/who /tmp/ramcache /tmp/diskusage
}
fi
shift $(($OPTIND -1))

sleep 1

done
```

Packet Capture Library (Control Channel Traffic)

PCAP reader (module)

pcapsave.py

```
from ryu.lib import pcaplib
from ryu.lib.packet import packet

frame_count = 0
# iterate pcaplib.Reader that yields (timestamp, packet_data)
# in the PCAP file
for ts, buf in pcaplib.Reader(open('test.pcap', 'rb')):
    frame_count += 1
    pkt = packet.Packet(buf)
    print("%d, %f, %s" % (frame_count, ts, pkt))
```

PCAP writer (module)

pcapread.py

```
from ryu.lib import pcaplib
class SimpleSwitch13(app_manager.RyuApp):
    OFP_VERSIONS = [ofproto_v1_3.OFP_VERSION]

    def __init__(self, *args, **kwargs):
        super(SimpleSwitch13, self).__init__(*args, **kwargs)
        self.mac_to_port = {}

        # Create pcaplib.Writer instance with a file object
        # for the PCAP file
        self.pcap_writer = pcaplib.Writer(open('test.pcap', 'wb'))

    ...

    @set_ev_cls(ofp_event.EventOFPPacketIn, MAIN_DISPATCHER)
    def _packet_in_handler(self, ev):
        # Dump the packet data into PCAP file
        self.pcap_writer.write_pkt(ev.msg.data)
```

Switch and Flow Table Statistics Collection

```
#!/usr/bin/bash

while true
do
curl -X GET http://localhost:8080/stats/table/1
curl -X GET http://localhost:8080/stats/flow/1

echo " "

sleep 30

done
```

APPENDIX – 6

List of publications

[1] T. Bakhshi and B. Ghita: *User Traffic Profiling In a Software Defined Networking Context*. Sixth International Conference on Internet Technologies and Applications, Wrexham, U.K., September 8-11, 2015. DOI: 10.1109/ITechA.2015.7317376 [Best paper award]

[2] T. Bakhshi and B. Ghita: *Traffic Profiling: Evaluating Stability in Multi-device User Environments.* The 30th IEEE International Conference on Advanced Information Networking and Applications, Crans-Montana, Switzerland, March 23-25, 2016. DOI: 10.1109/WAINA.2016.8

[3] T. Bakhshi and B. Ghita: *User-centric traffic optimization in residential software defined networks.* 23rd International Conference on Telecommunications, Thessaloniki, Greece, 14-16 May 2016. DOI: 10.1109/ICT.2016.7500389

[4] T. Bakhshi and B. Ghita: *On Internet Traffic Classification: A Two-Phased Machine Learning Approach*. Journal of Computer Networks and Communications, vol. 2016, Article ID 2048302, 21 pages, 2016. DOI: 10.1155/2016/2048302

[5] T. Bakhshi and B. Ghita: *OpenFlow-Enabled user traffic profiling in software defined networks.* 12th IEEE International Wireless & Mobile Comp. Conference, New York. 17-19 Oct 2016. DOI: 10.1109/WiMOB.2016.7763235

[6] T. Bakhshi and B. Ghita: *User-centric network provisioning in software defined data center environments.* 41st IEEE Local Computer Networks Conference, Dubai, 7-9 Nov 2016. DOI: 10.1109/LCN.2016.57